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Investigating complex phenomena: Bridging between systems thinking and modeling in science education

Edited by
Tom Bielik, Moritz Krell, Laura Zangori
and Orit Ben Zvi Assaraf

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Topic editors
Tom Bielik — Beit Berl, Israel
Moritz Krell — University of Kiel, Germany
Laura Zangori — University of Missouri, United States
Orit Ben Zvi Assaraf — Ben-Gurion University of the Negev, Israel

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Lianghuo Fan,
East China Normal University, China

*CORRESPONDENCE
Tom Bielik
✉ tom.bielik@beitberl.ac.il

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Editorial: Investigating complex phenomena: bridging between systems thinking and modeling in science education

Tom Bielik[1]*, Moritz Krell[2], Laura Zangori[3] and Orit Ben Zvi Assaraf[4]

[1]Faculty of Education, Beit Berl College, Kfar Saba, Israel, [2]IPN - Leibniz Institute for Science and Mathematics Education, Kiel, Germany, [3]Department of Learning, Teaching and Curriculum, College of Education and Human Development, University of Missouri, Columbia, MO, United States, [4]Department of Science and Technology Education, Ben Gurion University of the Negev, Beer Sheva, Israel

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Editorial on the Research Topic
Investigating complex phenomena: bridging between systems thinking and modeling in science education

1. Introduction

Complexity is all around us, from sub-atomic particles to distant galaxies. Modern technology and knowledge provide us with incredible abilities to investigate the complexity of systems of various kinds, such as human societies, biological ecosystems, chemical reactions, and physical interactions between energy and matter. In recent years, complexity has become prominent in most human local and global challenges, such as climate change, pandemic outbreaks, and sustainable energy sources. Understanding the complexity of phenomena is essential for scientific reasoning and sense-making, problem-solving in STEM, and technological tools development. Complexity pushes us beyond the dichotomic determinism of black-and-white classification and simple, straightforward solutions. It allows us to examine systems from different perspectives, explore alternative explanations, and keep an open mind while investigating phenomena—all of which lays at the heart of good critical thinking.

Certain key competencies are crucial for engaging constructively and responsibly with today's complexity challenges, including systems thinking and modeling. For instance, competency in systems thinking competency is suggested as one of the eight key competencies for sustainability (UNESCO, 2017). Most conceptualizations of systems thinking in science education encompass the ability of "system modeling" (e.g., Schuler et al., 2018; Mambrey et al., 2020), emphasizing the importance of modeling as a scientific practice for investigating and understanding complex phenomena (Passmore et al., 2017). Systems thinking and modeling are important competencies that provide students with essential tools when investigating complex phenomena and solving complex real-world problems. A recent literature review and bibliometric analysis reported a sharp increase in the number of studies about systems thinking in STEM education since 2016 (Bielik et al., 2023). However, most of the identified studies focused on higher education, while only a few focused on teachers or elementary students. There was also an increase in systems thinking studies, particularly on how the use of digital tools and modeling support system thinking competencies. This trend in studies about systems thinking and modeling in STEM education indicates a growing interest of the research community in these issues and the relevance of it for the complexity of today's challenges and problems.

Modeling is a key process of understanding complex phenomena as systems (Godfrey-Smith, 2006; Leonelli, 2007). Hence, it can be assumed that explicit knowledge about systems and system characteristics, such as metacognitive level awareness of how and why phenomena are conceptualized as systems, is beneficial for developing an initial system model and for deducing hypotheses related to specific structures or processes of the system (Verhoeff et al., 2008). Therefore, it can be further assumed that systems thinking and modeling are critical for science education in particular, and for STEM education in general when investigating complex phenomena. However, this mutually supportive relationship between systems thinking and modeling has not yet been deeply investigated in science education.

This Research Topic aims to advance current research focusing on bridging systems thinking and modeling when investigating complex phenomena in science education. It includes a set of studies that provide science education researchers, practitioners, and decision-makers with in-depth analyses and insightful findings that can promote our understanding of how to improve teaching and learning about complex phenomena and how to support students' systems thinking and modeling when engaging with complex phenomena in their science classrooms.

2. Theoretical background

2.1. Systems thinking in science education

In science education, systems thinking is generally defined as an approach to understand, explain, and interpret complex and dynamic phenomena, a learning strategy that explicitly considers system characteristics to explain and predict natural phenomena (Verhoeff et al., 2018). Systems thinking can be defined as the ability to recognize, describe, and model a complex phenomenon in its structure, behavior, and function *as a system*, including the metacognitive awareness about systems and system characteristics (Verhoeff et al., 2008; Riess and Mischo, 2010). Systems thinking is widely acknowledged as an important goal in science education that is necessary for "developing coherent understanding of complex biological processes and phenomena" (Verhoeff et al., 2018, p. 1). Three generally agreed-upon central systems thinking skills are proposed in the literature: identifying system organization, analyzing system behavior, and system modeling (Ben-Zvi-Assaraf and Orion, 2010; Mehren et al., 2018; Schuler et al., 2018; Mambrey et al., 2020).

Recent studies suggest three effective strategies for fostering systems thinking skills: modeling, cross-level reasoning, and use of systems language. For example, Rachmatullah and Wiebe (2022) found that computational modeling significantly improved middle school students' understanding of food web concepts and systems thinking. Düsing et al. (2019) found that when students were presented with integrative cases, where all levels of organization are considered through matter and energy transfers, they developed their cross-level reasoning ability. According to Krist et al. (2019), thinking across levels allows students to explain and make predictions about phenomena, and implicitly support mechanistic reasoning. Other studies showed that exposure to systems language helps students deconstruct a phenomenon to its characteristics and support the discussion on how patterns emerge from the interactions among system components (Gilissen et al., 2021; Nguyen and Santagata, 2021; Momsen et al., 2022).

2.2. Models and modeling in science education

Models are defined as epistemic tools for investigating and making sense of phenomena (Knuuttila, 2011). The developed model has to be evaluated for internal consistency and adequate representation of what was observed (Frigg and Hartmann, 2017). The model should allow the modeler to deduce predictions about how the system should behave under certain conditions by mentally or materially manipulating the model (Giere et al., 2006). These predictions can be tested by conducting empirical investigations. If the predictions turn out to be false, it is likely that the model is not accurate and should be rejected or revised and retested in an iterative cyclic process (Göhner and Krell, 2020).

Modeling competency is the ability to engage in the process of developing and using models for reasoning in science (Nicolaou and Constantinou, 2014; Upmeier zu Belzen et al., 2019). Hence, modeling is mostly defined as a procedural and epistemological competency (Upmeier zu Belzen et al., 2019). There is a wide consensus that developing modeling competency is an important goal of science education (Passmore et al., 2014; Chiu and Lin, 2019). When achieving modeling competency, students are expected to understand scientific concepts better, develop an appreciation of the nature of science, and advance in their mastery of the scientific process (Gilbert and Justi, 2016). Modeling has been identified as a key competency for investigating complex phenomena and developing hypothetical explanations and reasoning abilities (Passmore et al., 2017; Zangori et al., 2017). However, most studies in science education propose that students and teachers struggle with understanding models as hypothetical entities and research tools but rather hold representational views on models (Krell and Krüger, 2016; Gouvea and Passmore, 2017). When engaging in modeling for reasoning, one major challenge is the need for prior experiences and conceptual understanding of the investigated phenomenon on which a model can be built (Ruppert et al., 2017; Göhner et al., 2022).

2.3. Bridging between systems thinking and modeling when investigating complex phenomena

Systems thinking is conceptualized as a specific form of knowledge organization that allows a coherent understanding of complex phenomena (Verhoeff et al., 2018), while modeling is seen as a procedural and epistemological competency (Upmeier zu Belzen et al., 2019). Passmore et al. (2017) emphasize that the essence of modeling is to figure out "the behavior of systems in the natural and designed world" (p. 113). Developing system models is important for achieving advanced systems thinking (Hung, 2008; Verhoeff et al., 2008; Gilissen et al., 2020). For example, Hung (2008) showed that digital system modeling supported university students' systems thinking. Generally, computer modeling is suggested to be a powerful tool to support systems thinking by highlighting the central components of a system, making systems mechanisms tangible, easily running simulations to examine possible emerging outcomes, and helping students to grasp complex relationships within a system (Damelin et al., 2017; Bielik et al., 2021; Nguyen and Santagata, 2021).

From a cognitive psychology perspective, systems thinking and modeling are connected by their shared reliance on the concept of mental models. Mental models are internal cognitive representations of ideas, events, objects, or systems, which humans draw upon when generating external representations. These mental models result from an internal modeling process that includes constructing new information upon existing knowledge to build a stable model (Johnson-Laird, 2004). Goldstone and Wilensky (2008) describe the connection between modeling and complex phenomena, noting that developing a model of a situation requires to ground the interpretation of its components and extract a general principle from the situation. For the model to work, the mechanisms through which system components interact must be modeled. Godfrey-Smith (2006) describes the strategy of modeling (in biology) as gaining an understanding of a complex real-world phenomenon through investigating a simpler, hypothetical system (i.e., a model) that resembles it in selected aspects.

3. The contributions to this Research Topic

Several contributions to this Research Topic focus primarily on systems thinking when exploring complex phenomena (e.g., Bielik et al.; Sabel et al.; Tamir et al.). For example, Tamir et al. explored high school students' conceptualization of complexity while designing, assembling, and testing a nanosatellite. Findings show that the broader the participants' involvement was, the greater the progress they experienced in their systems thinking. Participants who stayed focused on a single subsystem of the nanosatellite did not show progress, while participants who involved themselves with several subsystems exhibited a more meaningful progress. The challenge of a multidimensional lens in students' understanding of complex systems was also found by Sabel et al., who pointed to students' difficulty in considering both natural and societal aspects of systems. They investigated undergraduate students' engagement in systems thinking and modeling using causal maps, focusing on identifying the factors that undergraduate students prioritize when considering causal relationships within an ecosystem. Although humans and human-related factors were included in the assignment picture, few students included human-related causes and effects in their causal maps or in the answers to the questions following the causal maps.

Other contributions in this Research Topic focus mostly on students' reasoning with models when exploring complex phenomena (e.g., Eidin et al.; Engelschalt et al.; Ryan et al.). For instance, Ryan et al. explored how computational tools mediated middle school students' mechanistic reasoning. They report that, as students interacted with the computational tools, their mechanistic reasoning about their models increased in complexity. Eidin et al. also expand research in a similar vein, exploring how different kinds of computational modeling experiences support secondary students' development of complex causal reasoning structures. The authors suggest "a system dynamics approach has the potential to encourage a more complex causal scheme of the phenomenon which the static equilibrium model was unable to support" (Eidin et al., p. 16). Engelschalt et al. explored the role of abductive reasoning when undergraduate students modeled complex systems. Their study participants used components of abductive reasoning in constructing models of biological systems, but using those components did not necessarily lead to generating scientific explanations. The authors suggest that individual may need an "interplay between abductive reasoning and systems thinking skills such as cross-level reasoning" (Engelschalt et al., p. 13) in which individuals may need to develop both systems thinking skills and cross level reasoning to consider causal relationships across system time and space.

Using computational models when exploring complex phenomena was another aspect investigated in several contributions in this Research Topic (e.g., Eidin et al.; Langbeheim et al.). These studies provided students and teachers with opportunities to engage with different modeling tools such as NetLogo (Langbeheim et al.) and SageModeler (Eidin et al.). For example, Langbeheim et al. found that participatory computational simulation can support 9th grade students' explanations of crowd evacuation counterintuitive required behavior provided students having prior opportunity to engage with a participatory simulation in a different context.

Finally, several publications explored the connection between systems thinking and modeling when exploring complex phenomena (e.g., Ke et al.; Lankers et al.; Peretz et al.). For example, Peretz et al. investigated the effect of an interdisciplinary online course on the development of pre- and in-service science and engineering teachers' systems thinking and modeling competency. Based on the findings of their qualitative case study, the authors propose that teachers need scaffolding to gain systems-related ontological knowledge (e.g., understanding systems language) before being able to apply this knowledge—as previously suggested to foster competency development in science education in general (e.g., Krell et al., 2023). Miller and Yoon developed modeling units on biological concepts (e.g., gene regulation) for students. They investigated how students' understanding of biological models influenced their understanding of complex systems. A regression analysis proposed that growth in students' meta-modeling knowledge predicts growth in complex systems understanding. For instance, a better understanding of the purpose of models provided students "with strategies to interpret data generated from multiple runs and to develop explanations of the system" (Miller and Yoon, p. 13–14). Similarly, students developed more elaborate theories about the investigated phenomena when understanding

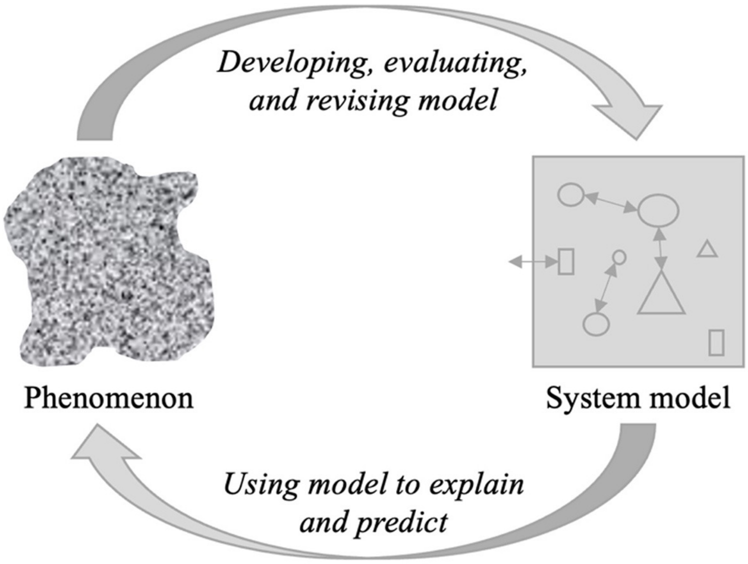

FIGURE 1
Idealized model of the cyclic and iterative system modeling process (based on Giere et al., 2006 and Göhner and Krell, 2020). A system model is developed, evaluated, and revised to represent selected relevant parts of the investigated complex phenomenon. The system model comprises of system characteristics (structures, processes, interactions, boundaries, and emergent states) represented by different shapes and arrows.

the dynamic and changeable nature of models because this led to more model manipulations.

4. Summary

Systems thinking and modeling are two intertwined competencies that support students when investigating complex phenomena. On the one hand, modeling is a procedural and epistemological competency that allows to develop and evaluate systems (Passmore et al., 2017). It is significantly supported by a coherent understanding of the respective phenomenon (Ruppert et al., 2017). On the other hand, systems thinking is viewed as a content-related competency (Verhoeff et al., 2018), which encompasses the ability of system modeling (Mambrey et al., 2020). However, there is still much to be researched about how these two competencies are empirically interconnected and how they interact when engaging students and science teachers when investigating complex phenomena.

In Figure 1, we present a model for the system modeling process, as reflected in the literature and the contributions to this Research Topic. In this model, a system model is developed, evaluated, and revised to represent and make sense of selected relevant parts of the investigated complex phenomenon. The system model comprises of system characteristics (e.g., structures, processes, interactions, boundaries, and emergent states), represented by different shapes and arrows in Figure 1. This model demonstrates the connection between systems thinking and modeling when investigating complex phenomena.

In summary, this Research Topic provides a collection of contributions focusing on modeling, systems thinking, and the connections between them when investigating complex phenomena. The contributions range from middle school to undergraduate students and pre- and in-service teachers, focusing on all science and engineering disciplines. We hope these contributions will further advance the understanding and promote the discussion among science education researchers, practitioners, and decision-makers regarding how to support teachers and students when engaging with complex phenomena.

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EDITED BY
Tom Bielik,
Freie Universität Berlin,
Germany

REVIEWED BY
Katherine Miller,
University of Pennsylvania,
United States
José Cravino,
University of Trás-os-Montes and Alto Douro,
Portugal

*CORRESPONDENCE
Yehudit Judy Dori
✉ yjdori@technion.ac.il

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Developing and assessing pre- and in-service science and engineering teachers' systems thinking and modeling skills through an asynchronous online course

Roee Peretz[1], Dov Dori[2] and Yehudit Judy Dori[1,3]*

[1]Faculty of Education in Science and Technology, Technion, Israel Institute of Technology, Haifa, Israel, [2]Faculty of Data and Decision Sciences, Technion, Haifa, Israel, [3]The Samuel Neaman Institute for National Policy, Technion, Haifa, Israel

Systems thinking and modeling are two critical 21st-century skills that teachers and educators are expected to impart to students, and students are expected to acquire and master them as part of their preparation to become literate citizens of a society and environment that is becoming ever more complex. Systems thinking is a thought process in which assumptions about interactions among interconnected elements of a system or a phenomenon can help predict the system's behavior, outcomes, and in the case of human-made artifacts, the value to its beneficiaries. Conceptual modeling involves the simultaneous visual and textual representation of one's ideas about a phenomenon or system in science or engineering. The qualitative study described here aimed to examine the effect of an online interdisciplinary asynchronous course on the development of systems thinking and conceptual modeling skills among pre- and in-service science and engineering teachers. Engaging in a qualitative case study with an exploratory orientation, we investigated how science and engineering teachers and teacher educators coped with (a) online learning of conceptual modeling and systems thinking using Object-Process Methodology in a food and sustainability context, and (b) developing an online assignment for teaching those skills to their students and assessing them. Research tools included the online assignment that the participants developed, a dedicated rubric for analyzing their assignments, accounting for use of modeling and systems concepts and the integration of sustainability and COVID-19 issues, a variety of thinking skills, visualizations and disciplines, and a mix of closed- and open-ended questions. Additionally, the participants' reflections were analyzed to characterize their sense of self-efficacy and academic progression. We characterize five teacher-developed assignment cases along with the related teachers' reflections, which exposed the benefits they had gained from the online course, as well as the systems thinking and modeling challenges they had faced. Analysis of the effect of the course with emphasis on the final task reveals that this approach is effective for developing the systems thinking and modeling skills of the teachers and serves as a catalyst for their professional development. The study offers a methodological contribution by providing a basis for evaluating teachers' assessment knowledge and skills using a six attributes rubric.

KEYWORDS
STEM teachers, systems thinking, modeling, online assignments, rubric, Object-Process Methodology—OPM

Introduction

As the world is becoming increasingly interconnected, a knowledge-based economy vigorously and ceaselessly drives globalization forward (Ritzer and Dean, 2019). Like any other social system, education systems need to prepare new professionals to tackle complex systems that characterize today's world and complex problems that arise as these systems, whether man-made or natural, affect humanity and the environment (Vivekanandan and Pierre-Louis, 2020). An example of a complex system is the National Healthcare Service (Checkland, 2000), or the stock market (Amaral and Ottino, 2004). These kinds of systems often combine people, technology, information, stakeholders, enablers, conflicting interests, and external influences. However, a flock of migrating birds or a termite colony are also (natural) complex systems (Amaral and Ottino, 2004). Common to all complex systems is the fact that they consist of a large number of parts or details that interact with each other and with their environment, making the system highly adaptable, and they are not organized based on a known external organization principle (Amaral and Ottino, 2004). Unlike simple or even complicated systems, complex systems are hardly amenable to predicting long-term performance or outcomes. Differences between simple, complicated, and complex systems can be found in detail in Amaral and Ottino (2004).

A thought process for examining interconnected elements within systems to predict their behavior (Dori, 2016), systems thinking is a higher-order thinking skill that is crucial to responding to the challenges and complexities of the 21st century (Sterman, 1994). A complex system, the National Healthcare Service, for example, requires systems thinking for designing or changing it (Checkland, 2000).

Despite its emergence from the complex reality, systems thinking is neither natural nor innate, and often it is even counterintuitive (Gharajedaghi, 2011). Various educational practices must therefore be adopted in order to foster systems thinking. Leading among these practices are systems modeling, interdisciplinary learning, and context-based learning. These are recognized as essential to 21st-century learners according to various educational frameworks in science, technology, engineering, and mathematics (STEM) disciplines (e.g., Partnership for 21st Century Skills, 2004; NGSS Lead States, 2013; Accreditation Board for Engineering and Technology, 2021).

Yoon et al. (2017) discussed the crucial position of professional development programs for teachers. These are imperative to ensure successful instruction about complex systems and increase teachers' awareness of using models and modeling in science education. Such professional development programs are equally vital for pre-service teachers. The research described in this paper offers an in-depth view of the challenges and opportunities involved in a conceptual modeling-based online interdisciplinary course. We also investigated the learning process pre- and in-service science teachers went through as they were studying this course, as well as their learning outcomes. We focus on imparting the basis for systems thinking skills and their assessment, followed by self-developed assignments as the final stage of the learning process of the course participants.

Theoretical framework

In this section, the theory underlying systems thinking and conceptual modeling is presented with a focus on their relations to STEM education and teachers' understanding of these skills.

Systems thinking: Definitions and recent research

Scholars have defined systems thinking differently, but many of the definitions share important commonalities. Arnold and Wade (2015) claimed that the breakdown of systems thinking into its main components may facilitate its teaching and assessment, which is consistent with other studies (e.g., Assaraf and Orion, 2005; Lavi et al., 2019). The main systems thinking components include (1) recognizing interconnections, (2) understanding feedback loops, (3) understanding the system's structure, (4) differentiating stock and flow variables, (5) understanding non-linearity, (6) understanding dynamic behavior, (7) reducing complexity by conceptual modeling, and (8) recognizing different scales of systems (Arnold and Wade, 2015). These components are common to different frameworks for systems thinking (e.g., Assaraf and Orion, 2005; Stave and Hopper, 2007; Lavi et al., 2019). Arnold and Wade (2017) also divided systems thinking into two facets, extending beyond just understanding systems: *Gaining insights*, which relates to approaching systems from the outside and investigating them from several viewpoints, and conversely *using insights*, which is, broadly speaking, approaching systems from the inside, such as rearranging their structure. Each facet encompasses a specific set of techniques that may be used in parallel or in series, constantly strengthening each other.

In this study, we define systems thinking according to Dori et al. (2020) as thinking that involves examining the connections and interactions between elements within a system or phenomenon to understand how they function to influence behavior and to determine the value of human-made artifacts for their intended beneficiaries.

Although a considerable number of studies have examined the development and assessment of systems thinking in different STEM education settings (e.g., Assaraf and Orion, 2005; Gero and Zach, 2014; Lavi and Dori, 2019), the teaching and instruction of this important concept are at best mainly implicit, and students struggle when faced with a topic that requires a high degree of systems thinking (Arnold and Wade, 2017; Chen et al., 2019; Talanquer, 2019). Explicit instruction about complex systems and systems thinking concepts can lead to the deepening of knowledge and understanding and the transfer of these concepts among students (Goldstone, 2006; Hung, 2008), as well as teachers (Yoon et al., 2017). Rates et al. (2022) found that explicitly teaching students about complex system concepts was more effective than self-monitoring scaffolding, which is important in its own right. They referred to explicit learning as "ontological scaffolding," building on the work of Jacobson et al. (2011). In this context, ontology can be defined as the explicit formal specification of the nature and structure of a system, described in terms of categories and relations (Guarino et al., 2009). Chowdhury (2023), conversely, argued that instead of enclosing systems thinking in a framework that is loaded with professional language, considering systems thinking as a cognitive skill might lead to its greater acceptability by a wider target audience. Verhoeff et al. (2018) claimed that given the current research knowledge of how to foster higher-order systems thinking skills and the conflicting curricular considerations, a complete curricular program of systems thinking teaching is not yet possible. Higher-order systems thinking skills include the ability to understand nonlinearities and cyclicity in systems and recognize complex patterns and relationships, and predict future behavior from current systemic interactions (Assaraf and Orion, 2005; Verhoeff et al., 2018). Another key higher-order systems thinking skill is modeling (Stave and Hopper, 2007).

Conceptual modeling and STEM education

Modeling can facilitate the understanding of complex systems, as well as their explicit teaching and assessment (Hung, 2008; Dori, 2016). Modeling languages and methodologies are important for expressing what complex systems do, why and how they do it, and what is required for that purpose. Researching natural systems or designing human-made ones often involves complexities that cause a significant cognitive load on the learner or designer. By modeling, unnecessary complexity can be reduced, while necessary complexities can be expressed and emphasized (Dori, 2016). To engage students in model-based complex systems thinking, their teachers must master it first (Yoon, 2008; Krell and Krüger, 2016), and these practices must be systematically integrated into the curriculum (Rosenkränzer et al., 2017; Talanquer, 2019).

Science and technology education is largely driven by models and modeling (Gilbert et al., 2000). Merriam-Webster (n.d.) online dictionary defines the verb "to model" as *"to produce a representation or simulation of (something)."* In the same spirit, *models* are representations or simulations of something—a phenomenon, a system, the desired product, or even an idea or event (Gilbert et al., 2000). Unlike the internally generated mental models (Johnson-Laird, 1983), *conceptual models* are external, or 'expressed' (Gilbert et al., 2000) representations that can be shared within a given group (scientists, engineers, teachers, etc.) and are coherent with the accepted knowledge of that group. Conceptual modeling is of high value to STEM education as it reflects the transition from models that are personal, incomplete, and lacking firm boundaries, to more precise and complete representations of the accepted knowledge (Norman, 1983; Gilbert et al., 2000). However, conceptual modeling is seen from a didactic point of view as complex and difficult to master by learners and teachers (Rosenthal et al., 2019).

As early as 1989, Richard Mayer concluded his article named *Models for Understanding* with the statement that *"One particularly exciting avenue concerns the role of interactive computer graphic simulations as a vehicle for expanding the power of conceptual models"* (Mayer, 1989, p. 61), backing the statement by the work of White (1984). The conceptual modeling language and methodology used in the current study is OPM—Object-Process Methodology (Dori, 2016)—which is ISO[1] 19,450 and has been implemented in a dedicated online modeling platform, as elaborated in the Materials and Methods section. OPM has been researched over the years in educational contexts (Lavi and Dori, 2019; Akiri et al., 2020; Peretz et al., 2023), and it is the most researched model-based systems engineering modeling method (Dong et al., 2022). Due to its simplicity, intuitiveness, and bimodality (Dong et al., 2022), as well as its domain-independent nature, OPM is most suitable for teaching, learning, and assessment of learning in various disciplines (Dori, 1995). However, a qualitative evaluation of an OPM-based learning process has not yet been carried out. In this research, OPM has served to assess teachers' systems thinking-related knowledge and abilities as they develop learning materials based on inherently interdisciplinary system ideas.

Modeling is an activity that inherently involves various aspects of the modeled system or phenomenon. This may increase the opportunity for interdisciplinary collaboration between STEM disciplines in authentic settings and, in turn, promote successful integration between and outside STEM disciplines (Hallström and Schönborn, 2019). From the opposite perspective, systems thinking may be fostered through interdisciplinary learning processes, as reported by Gero and Zach (2014) and others (e.g., Ackerman and Perkins, 1989). This is especially important in educational environments that are often disciplinary, and when dealing with inherently complex and multifaceted issues, such as sustainability (Riess and Mischo, 2010; Harsaae et al., 2022). Interdisciplinarity is usually defined as the integration and communication across at least two different academic disciplines (Frodeman, 2013). For example, considering waste production and particulate emission, food production requires an understanding of biology, chemistry, and environmental aspects. Engineering and economic aspects need to be considered too in order to comprehend engineered systems such as food production ones. The interdisciplinary approach is already a *fait accompli* in STEM research and STEM industries, but its application to STEM education is still superficial (Klaassen, 2018).

Teachers' understanding and teaching of complex systems

The ability of teachers to engage in the instruction of systems thinking through conceptual modeling in an interdisciplinary learning environment depends, among other things, on their ability to assess this kind of learning in a relevant context-based learning setting (Pilot and Bulte, 2006). As assessment knowledge depends on pedagogical-content knowledge, PCK (Avargil et al., 2012; Tal et al., 2021), both the teachers' instructional abilities and the content knowledge have to be at a sufficiently high level to fundamentally change the teaching of systems thinking and conceptual modeling as standalone disciplines and as part of STEM teaching (Rosenkränzer et al., 2017). Yoon et al. (2018) pointed out that there is a lack of research on what teachers need in professional development activities concerning complex systems.

Research aim and research questions

In our study, we used a case study approach to investigate the knowledge and ability teachers need to develop conceptual modeling-based online assignments after being introduced to basic system concepts through an OPM-based online learning process. Engaging in a qualitative case study with an exploratory orientation, we investigated the following two research questions (RQs):

RQ1: How did online learning of conceptual modeling and systems thinking in the context of food production and sustainability affect the STEM teachers' performance?

RQ2: What was the level of each of the six attributes—conceptual modeling, systems thinking, sustainability and COVID-19, thinking skills, visual representations, and interdisciplinarity—as expressed in the online assignments developed by the STEM teachers for their students?

1 International Organization for Standardization.

Materials and methods

Rather than generalizing to a wider population or testing a hypothesis, case studies aim to provide a rich, detailed understanding of a specific case. In a collective case study, the phenomenon of interest is researched through selected cases that have both similarities and differences. For each case in the study, the researcher considers its key circumstances, particularity, and complexity (Stake, 1995, p. xi). We implemented a descriptive collective case study to examine how pre- and in-service STEM teachers of various backgrounds approached an online, model-based interdisciplinary learning process.

Research context and procedure

The soaring complexity in almost every aspect of life calls for proper preparation to enable teachers to tackle this reality (Rosenkränzer et al., 2017). To this end, we developed an asynchronous interdisciplinary online learning process, containing four food-related modules that aim to both develop and assess systems thinking and conceptual modeling. Upon completing the learning process, the participants were asked to develop their own assignments as the final stage of their learning process. They were instructed to choose a topic related to food production and combine in their assignment a variety of representations and thinking skills. They were also instructed to include at least one aspect of sustainability and one related to COVID-19. All the assignments had to be accompanied by corresponding conceptual OPM models the participants had to create from scratch.

OPM

OPM is a model-based systems engineering methodology and language (Dori, 2016). Conceptual models created in OPCloud, a web-based collaborative software environment for modeling in OPM (Dori et al., 2019), contain only things and links. In OPM, the link types are divided into two main groups: structural and procedural (see the scoring rubric in the Conceptual Modeling subsection regarding link types and their impact on the scoring). A thing may be a process or an object, each representing a basic unit of knowledge, namely a concept, whereas links represent the relations between things (Dori, 2016). OPM includes both graphical and textual modalities, with the latter automatically generated while the former is created by the modeler. OPM models are organized in a hierarchical tree structure using object-process diagrams (OPDs. See Table 1 for acronyms). The system diagram, SD, is the OPD at the highest level of abstraction in this hierarchy, and it can be further refined into a more detailed view called SD1. This more detailed OPD elaborates on the structural, behavioral, and functional aspects of the system described in SD. An example of SD and its corresponding OPL is presented in Figure 1. Although the refinement process can go on to more detailed levels in other diagrams of the model (SD1.1, SD1.2, SD1.2.1, and so on), in this research the refinement did not go beyond SD1. As OPM is bimodal, each element that is added to the graphical representation in the model, OPD, simultaneously generates a corresponding sentence in object-process language (OPL)—a subset of English or any other natural language. This provides for ongoing metacognitive reflection while building the OPM model and not just retrospectively. Consequently, each OPL paragraph of any given OPD expresses textually the same model facts that the OPD expressed graphically (Dori, 2016).

TABLE 1 List of Object–Process Methodology-related acronyms.

Acronym	Meaning
OPM	Object-Process Methodology
OPL	Object-Process Language
OPD	Object-Process Diagram
SD	System Diagram

Figure 1 presents the Chocolate Producing process which is part of the fourth module of the learning process. This OPD formed the background for the questionnaire of the fourth module, in which respondents were required, among other questions, to determine the kind of the missing link marked with the letter L. As in any OPD, rectangles represent system objects, ellipses represent processes, and the rounded-corner rectangles inside an object represent states, which are situations at which that object can be. The OPM default colors are blue for processes, green for objects, and gold for states, both in the OPD and OPL. The black words in the OPL are reserved phrases that unambiguously describe in text all the modeled facts. For example, the sentence at the bottom of the OPL paragraph reads "Chocolate Eating consumes Chocolate." This is the unambiguous textual description of the model fact that is expressed graphically within the red rectangle: the object Chocolate linked to the process Chocolate Eating using a consumption link—the arrow from that object to the process.

Research participants

All pre- and in-service teachers were recruited at the Technion, Israel Institute of Technology. We used critical case sampling, which is a purposive sampling method, in which researchers aim to gain deeper understanding of the process being examined by selecting cases that are of special importance to the study. This guideline enabled obtaining a diverse set of critical cases within the sample (Ritchie et al., 2003).

The participants were both in- and pre-service teachers enrolled in the Technion's Faculty of Education in Science and Technology. Some participants took part in the research to receive academic credits within a course or a research project, while others took part after receiving a personal request. After excluding those who did not complete most requirements, 12 teachers made up the initial sample, of which nine were women (Table 2), none of whom had previous experience with OPM. A small minority of the 12 participants had superficial and sporadic previous familiarity with basic system concepts, such as function, structure, behavior, and purpose.

Case studies of five STEM teachers

Of the 12 teachers above, we chose five to form our collective case study, two of whom were men. While case studies in education

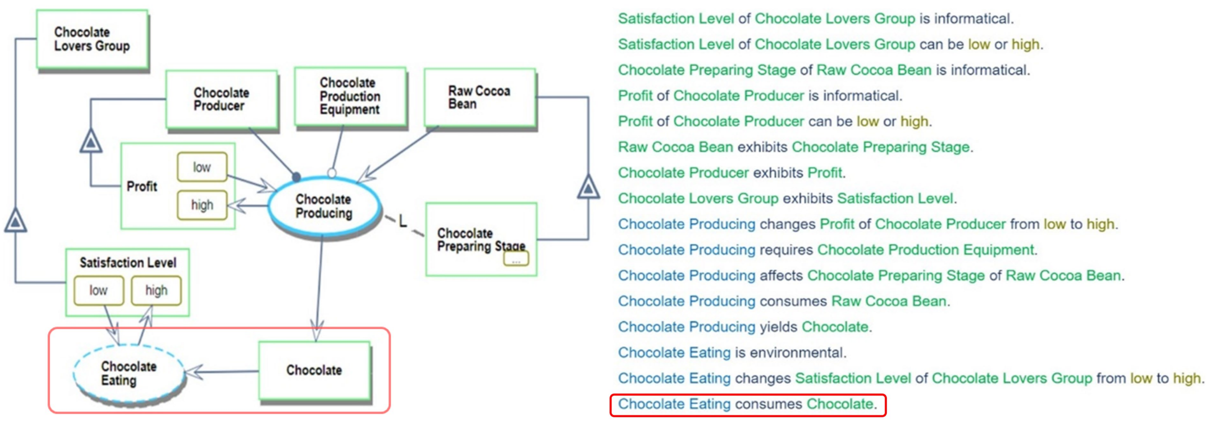


FIGURE 1
SD level OPD and its corresponding OPL of Chocolate Producing process.

TABLE 2 The background of the 12 participants that made up the initial sample.

#	Pseudonym	Age (years)	Academic background (first degree completed)	Teaching discipline	Teaching experience (years)	Teaching experience earned in:
1	Ron*	<50	Electrical engineering	Physics	5–10	High school
2	Danielle	41–50	Management and Economics	Science and management	<10	Academy and high school
3	Anna	<50	Biology	Science and Mathematics	<5	Elementary school
4	Eli	21–25	Mathematics and computer science	Mathematics	<5 (Pre-service)	High school
5	Romy	41–50	Industrial engineering and management and computer science	Industrial engineering and management	<5	Technology college (non-academic)
6	Jenny	41–50	Industrial engineering and management	N/A	N/A	N/A
7	Ben	31–40	Chemical engineering	Chemistry and physics	<5	High school
8	Benny	<50	Chemistry	Chemistry	<10	High school
9	Jasmin	41–50	Chemistry	Chemistry	<10	Technology college and academy
10	Suzy	<50	Chemistry	Chemistry and science	5–10	High school
11	Sofía	41–50	Environmental science	Environmental science and chemistry	5–10	High school
12	Yulia	41–50	Environmental chemistry	Chemistry	5–10	Technology college

*A name in bold indicates that the participant was among the five selected for the case analysis.

typically include at most two or three cases, we included five cases to increase generalizability and the likelihood to gain diverse insights. We based our selection on differences in their performance during the study and their different backgrounds, as well as the similarities among them: all five were current or future STEM teachers who completed the online learning process we had developed. One of them (Eli) was a pre-service teacher, while the other four were in-service teachers. All five held a teaching certificate. As shown in Table 2, the five represented different age groups, academic backgrounds, teaching areas, seniority, and levels of teaching.

The online learning process

According to our previous research (Akiri et al., 2020; Peretz et al., 2023), most pre- and in-service STEM teachers lack basic systems thinking and conceptual modeling proficiency. These deficiencies have been noted also by Yoon et al. (2017) and Arnold and Wade (2017). Therefore, it was necessary to provide the teachers with the basics of systems thinking and conceptual modeling to enable them to create for their students assignments that involve these skills. To this end, we developed a food-related four-module online learning process in the form of an elective professional development course for STEM teachers. We chose food-related topics because they are interdisciplinary and complex (Jagustović et al., 2019) while also being highly relevant. The online learning was carried out asynchronously at a pace adapted to the limitations and constraints of each learner. Indeed, the time it took the teachers to complete the learning process ranged from a few days to a few weeks. We hypothesized that following the implementation of the learning process, the teachers would internalize instructional and assessment principles, and not only the content area we explicitly sought to develop, i.e., conceptual modeling and systems.

Besides establishing a basic knowledge of conceptual modeling and system concepts for the participating teachers, their average score of the responses to questions included in the modules provided us with an indication of the systems thinking level of each participant, as elaborated below. Although the learning process included conceptual modeling requirements, we did not use their scores to assess the conceptual modeling level. This is because the modeling requirements were highly structured, so they could not serve as a measure of the teachers' ability to create model diagrams from scratch, as explained in the section "Developing Online Assignments" below.

Systems thinking

The learning process that preceded the assignment development was based on studying four modules whose content was chocolate production and cod fish value chain. Each module included a questionnaire and a quiz. The score for each questionnaire and quiz was calculated as the percentage of correct answers. Closed-ended questions were automatically scored by using Google Forms, while open questions were checked manually. The content of each module is presented in Table 3. A detailed description of the content included in the learning process appears in Akiri et al. (2020) and Peretz et al. (2023).

The principle that guided us in designing the process is a gradual increase in the difficulty level. The difficulty level gradually increased from one module to the next, as well as within each module. The questions' complexity increased gradually, requiring more advanced thinking skills as the modeling principles and systems concepts gradually became more difficult to internalize. For example, while the first module focused on the introduction of OPM entities—processes, objects, and states, in the fourth module learners were exposed to synchronous versus asynchronous processes and their different refinement mechanisms into more detail levels. Previous research we conducted (Akiri et al., 2020; Peretz et al., 2023) suggests that the online modules, which cover cross-disciplinary processes, can serve as a foundation for developing and assessing students' and teachers' systems thinking.

Developing online assignments

In the assignments that the participants developed, they had to apply on several levels what they had learned earlier. The first level was modeling the content knowledge they had acquired, i.e., system and modeling concepts, which provided the common basis for all the ensuing assignments. The participants had to integrate into their self-developed assignment conceptual models that they had created. At the second level, the participants had to apply assessment knowledge while integrating a variety of thinking skills and visual representations. Thirdly, they had to integrate interdisciplinary topics, specifically sustainability and COVID-19, into the topic they had chosen to contextualize their assignment.

TABLE 3 The content of the four modules that formed the learning process.

Module	Content description
1	- Introduction to OPM. - Identifying objects, processes, and states in a system.
2	- System aspects: function, structure, and behavior. - Structural relations, state transitions, system aspects, and OPM modalities.
3	Understanding the System Diagram (SD): System Purpose – beneficiary and benefit, system function; and process enablers – agents and instruments.
4	- Diving into the details: the first detail level (SD1) of the OPM model, divided into major subprocesses. - Synchronous vs. asynchronous processes.

In analyzing the assignments, we focused on six attributes: (1) conceptual modeling, (2) systems thinking, (3) visual representations, (4) thinking skills, (5) sustainability and COVID-19, and (6) interdisciplinarity. While conceptual modeling and systems thinking were explicitly taught during the learning process, visual representations, thinking skills, and interdisciplinarity were supposed to be internalized implicitly, following the completion of four learning modules that included multiple visual representations, diverse thinking skills, and different disciplines. No explicit or implicit instructions were given in the learning modules on integrating sustainability and COVID-19 issues into the assignments except that this was a requirement for the assignment development. Since the learning process occurred during the pandemic peak period and while the energy crisis was frequently discussed in the news, we were interested in testing the ability of the participating teachers to integrate these issues into each teacher's broader chosen context.

Table 4 presents the scoring rubric for the six analyzed attributes. As noted, the systems thinking score was based on the learning process rather than on the developed assignments. This is so because the systems thinking learning process was more extensive and included more aspects related to systems thinking than the other five attributes, whose scores were based on the assignments the teachers had developed.

As recommended by Kaczynski et al. (2008), the scores for the six attributes are presented in the Results section as spider charts to enhance qualitative inquiry in instructional settings. This kind of chart generally considers six related attributes, each with a

TABLE 4 Scoring rubric for the assignments developed by the teachers.

Scoring Attribute	Low 1 point	Intermediate 2 points	High 3 points
Conceptual modeling	The OPM score ranges from 0 to 4	The OPM score ranges from 5 to 7	The OPM score ranges from 8 to 10
Systems thinking (ST)	The ST score ranges from 0 to 4	The ST score ranges from 5 to 7	The ST score ranges from 8 to 10
Sustainability and COVID-19	Negligible reference to both COVID-19 and sustainability	At least one aspect of COVID-19 or sustainability is integrated into the task, but not both	At least one aspect of COVID-19 and one aspect of sustainability are integrated into the task
Thinking skills—understanding, applying, comparing, evaluating and designing	Only one thinking skill is included	Two to three thinking skills are included	Four or more types of thinking skills are included, with at least one "designing" activity
Visual representations—text, tables, figures, diagrams, videos, links, and illustrations	Two or fewer representations are included	Three to four representations are included	Five or more visual representations are included
Interdisciplinarity—chemical, physical, biological, economic, environmental, technological, and societal aspects of the chosen topic	Only one aspect is included	Two aspects are included	Three or more aspects are included

Six attributes with a maximum score of 3 points each, with a possible maximum score of 18 points per assignment.

five-point scale, so we made a minor adaptation of the scale to be 1–3 instead of 1–5 to match our assignment assessment rubric (See Table 4).

Conceptual modeling

To assess the participants' ability to create conceptual OPM models, we explicitly instructed them to include in their self-developed module a complete OPM model with two OPDs: SD (system diagram)—the top-level, abstract system view, and SD1—the first detail level, in which the main process from SD is zoomed into. We asked them to also supplement each OPD with its automatically generated textual OPL sentences, in a structured subset of English. The entire model had to be included even if not all of it was needed for the assignment they had developed. In some cases, the model itself was the answer to a modeling requirement in the assignment. The conceptual modeling score was calculated based on a modified version of the Systems Thinking Assessment Rubric—STAR, developed by Lavi et al. (2019), and presented in Table 5.

Trustworthiness

Following basic criteria for trustworthiness in qualitatively oriented research (Guba and Lincoln, 1982), we took some measures to establish the trustworthiness of our study's findings. To triangulate our data and enhance the clarity and depth of our findings, we utilized an array of data sources, including questionnaires featuring both open- and closed-ended questions, conceptual models, self-developed assignments, and written reflections. To facilitate the reproduction of our research process by future researchers, even if their findings may vary, a comprehensive description of the research process is provided. All three authors took an active part in the research to minimize the researcher bias, each bringing their own unique perspective to the research. Lastly, to minimize the positive confirmation bias (Nickerson, 1998), we used a pre-registered research design that may reduce interpretation bias, as data collection occurs after the research plan has already been established.

Ethics

All participants had to agree to an informed consent form at the beginning of the learning process. Choosing the "disagree" option in the informed consent section ended the process so that it was not possible to answer any further questions, let alone continue developing an assignment. All the names presented in this article are pseudonyms, and no detail that could identify participants in any way was included. The research process was approved by the Technion's Behavioral Sciences Research Ethics Committee, Approval #2020–165.

Results

In the first part of this section we present the five cases—assignments, each developed by one of the participants, a pre- or in-service STEM teacher. Each case is presented with segments from its developed assignment and OPM model, along with the respective analysis. The analysis is performed both quantitatively, through the modified systems thinking assessment rubric to assess the OPM model quality, and qualitatively, via a description of the development process. The second part of the Results section presents a collective analysis of the six predefined attributes for each participant, both through spider charts and a table explaining each scoring.

Five selected cases: Focusing on conceptual modeling and systems thinking

We start with the findings relating to systems thinking and conceptual modeling of each case separately. The five participant names below are pseudonyms.

TABLE 5 Modified Systems Thinking Assessment Rubric (STAR).

Aspect	Attribute	Expected implementation of the attribute	Scoring
System Aspect			
Function	A1-Intended Purpose	Beneficiary and benefit are linked with the correct link (Exhibition-Characterization), and both are phrased correctly according to the context.	Both beneficiary and benefit are absent – zero points. Only one of them (beneficiary/benefit) is used or both without a correct link – one point. Both beneficiary and benefit are used and linked, but not accurately phrased – two points. Both beneficiary and benefit are correctly used – three points.
	A2-Main Function	Exactly one main process, which transforms at least one object, all of them phrased correctly according to the context. For SD1, At least three sub-processes, with the same specification as above.	No main process, or the main process which is irrelevant to the context – zero points. The main process is correct but transforms no object(s) or is wrongly phrased – one point. The main process transforms at least one object, phrased, and linked correctly – two points.
Structure	A3-Structural relations	Correct use of at least two out of four kinds of links between objects or between processes.	No links- zero points. One link or more – one point.
	A4-Level of Complexity	Both SD and SD1 are included.	Only one level included – zero points. Both levels included –one point.
Behavior	A5-Procedural relations	Correct use of at least three procedural links between objects and processes	Less than two links – zero points. Two links or more – one point.
Model Aspect			
Clarity	A6-Model readability	The layout of all the model diagrams is organized to facilitate its understanding.	1 – links do not cross things, things do not occlude each other, 2 – minimal links cross each other, 3 – entity (object, process, state) text is complete and words are not split. At least one violation – zero points. All fulfilled – one point.
OPL	A7-OPL main process procedural sentences	1. The beneficiary is linked with an agent link, e.g., "Winemaker handles Harvesting." 2. The operand is linked with a correct result/effect link, e.g., "Bread Making yields Bread Loaf," or: "Harvesting changes status of Grape from on tree to picked." 3. An instrument or consumption link used correctly, e.g., "Bread Making requires Mixing Machine," and "Bread Making consumes Flour and Water."	No more than one of the three sentences is present or no OPL is attached at all – zero points. Two or three sentences (out of three) are present – one point.

Case 1—Anna: A novice biology teacher

Anna is a novice biology teacher with an academic background—a master's degree in biotechnology and a teaching certificate in biology. She has 2 years of experience as an assistant teacher in an elementary school. It took her about 3 months to complete the learning process and about a month and a half to develop the assignment.

The topic she chose for her assignment was tofu production and its by-products. She explained that it was not a random choice of the first food production process she encountered online, but a result of personal experience: She makes and sells homemade tofu and okara—soy pulp, the insoluble phase of crushed soybeans that remains after filtering. Therefore, as she stated, she knows the process inside out and feels connected to it. She emphasized that she had chosen this topic because the assignment she was asked to develop seemed complex to her, and her commitment to the process and the final product called for choosing a relevant, familiar topic. She began her assignment by introducing tofu and its production: its geohistorical roots, its production method, its nutritional-chemical composition, and its virtues. She then focused on the different stages of tofu making from a food engineering perspective, starting from raw soybeans, through soy milk, to the pasteurized product ready for marketing. Figure 2 presents selected segments from her assignment. As can be seen in this figure, she included a variety of thinking skills and used diagrams alongside the text. However, the relevance and integration of sustainability and COVID-19 into the tofu context were insufficient.

The top-level OPD which Anna created focused on okara fermentation. In SD1 it is refined into four subprocesses, but not all of them are related to the okara fermentation. For example, the first subprocess, Cooking, precedes the fermentation process. Her model received a score of 6/10, with points deducted due to insufficient definition of the system's purpose and little variety in link types. Table 6 provides the scoring of this OPM model with explanations according to each attribute included in the modified STAR.

In her reflection, Anna wrote that conceptual modeling helped her to better define boundaries when it comes to complex systems.

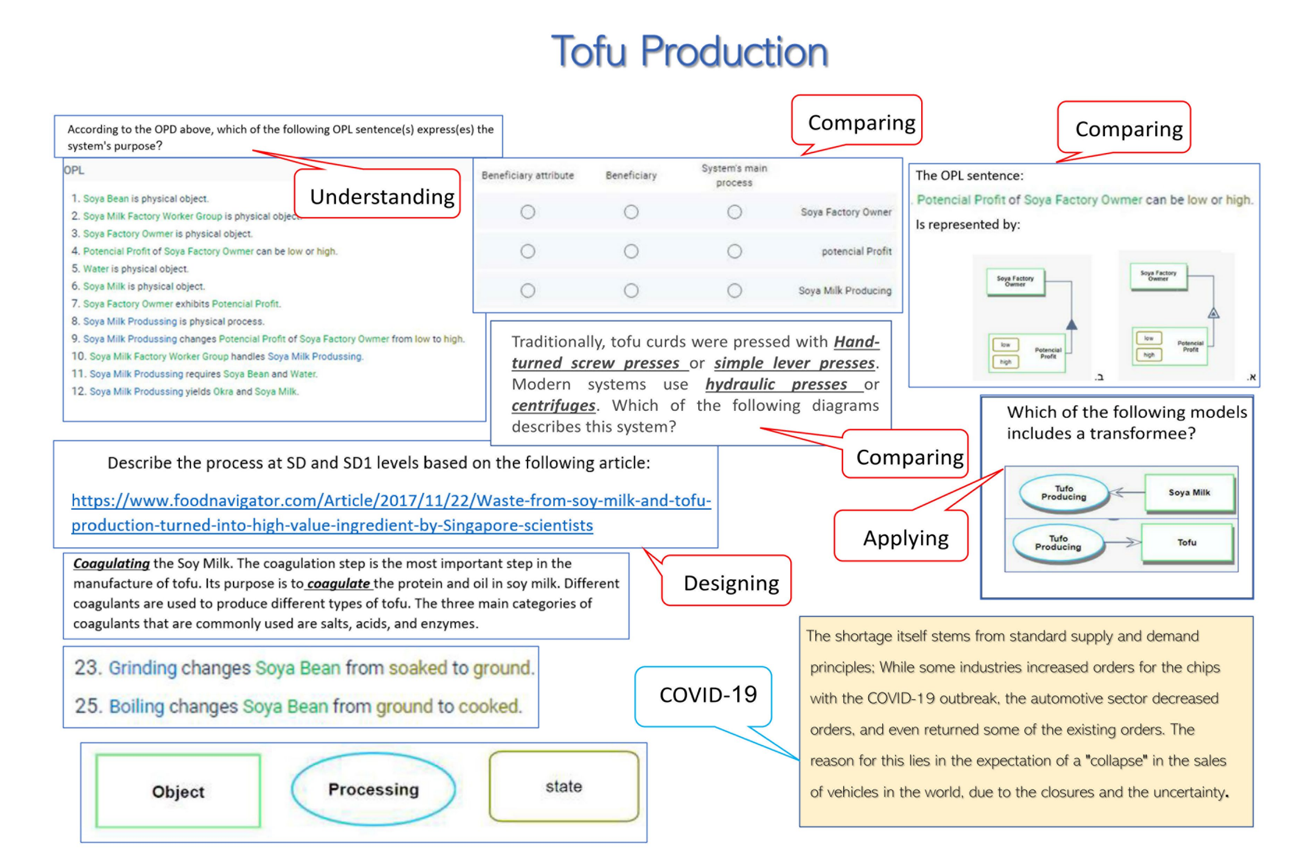


FIGURE 2
Selected segments from Anna's tofu production assignment.

She had no background in modeling or systems, so at the beginning of learning, she had difficulty finding herself given the unfamiliar territory of system concepts and system-related language. She pointed out that she had "*no relevant background at all,* […] *it was difficult for me to focus on the unfamiliar concepts and unique terminology involved.*" The OPM itself, she stated, was understandable as soon as she was aware of the background and terminology. The most difficult concept for her to understand was "*defining the various levels and aspects of the system as reflected in the OPM model.*" This issue was reflected in her model (Table 5) by not modeling the beneficiary, and by the somewhat vague definition of the benefit. Since human-made systems are usually designed to benefit one or more beneficiaries—the stakeholders who extract value and benefits from the system, the purpose cannot be described in OPM models and modeling in general without including both the system beneficiaries and the benefit it provides. She needed help a couple of times during the learning process in using OPCloud to create the model, and this was provided online by one of the authors.

Regarding the assignment Anna developed, she noted that it required a lot of knowledge of various kinds, and even though she is very knowledgeable about tofu and okara production, searching online for relevant material on the processes was necessary to model them appropriately. The learning process, from her experience, gave her "*a clear framework for planning the learning,* […] *which in turn helped me even more to understand the system I chose for the assignment. The modeling allowed me to better plan and design my assignment and not only to create a better model.*"

Case 2—Eli: Pre-service mathematics teacher

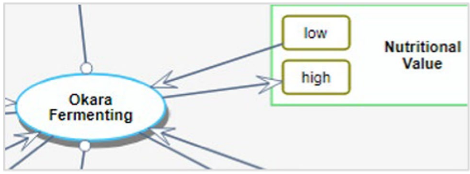
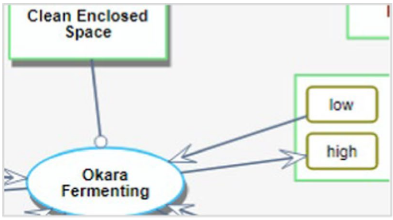
Eli is a pre-service mathematics teacher who is currently pursuing his mathematics and computer science bachelor's degree combined with a mathematics teaching certification. It took him about 2 weeks to complete the learning process and about a month to develop his assignment. His assignment topic was gummy bears production, starting with the technological and food engineering aspects of the process: from mixed ingredients to soft candies ready for packing. Figure 3 presents selected segments from his assignment. The figure might explain why his assignment score was 18/18: Eli included diverse thinking skills—basic alongside advanced ones. He combined sustainability and the pandemic in an integrative and context-relevant way, relating to a variety of disciplines.

The main process he chose to model in the assignment is the Gummy Bears Production. Eli produced a high-quality model in all three major system aspects—function, structure, and behavior, as well as model clarity.

The layout of elements in his model diagrams were perfectly organized, without a single link crossing another and without spelling mistakes or incorrect phrasing in terms of OPM. His awareness of the model readers' need to understand his model was higher than that of others, as expressed in his reflection regarding suggestions for improvements that the participants had:

"*When we convince ourselves that we can think about components [of the system] and communicate them, it's time to start modeling.*"

TABLE 6 Scores and explanations for the OPM model created by Anna.

Attribute	Scoring and explanation	Examples in the model (screenshots)
A_1-Intended Purpose	1/3. A beneficiary is missing and the benefit, Okara at state renewed, is vague	
A_2-Main Function	2/2. The main process, Okara Fermenting, transforms (changes) four objects: Nutritional Value, Flavor, Food Waste, and Okara	
A_3-Structural Relations	0/1. One generalization-specialization link was incorrectly used. Properties and attributes in OPM are denoted by an exhibition-characterization link and not as done here	
A_4-Level of Complexity	1/1. Both SD and SD1 are included	n/a
A_5-Procedural relations	0/1. Input-Output link-pairs and instrument links. No agent links were used at all. Three effect links were wrongly used	 
A_6-Model readability	1/1. No points were taken off for misspellings in English	n/a
A_7-OPL main process procedural sentences	1/1. Two out of three sentences are included	Okara Fermenting changes Flavor from poor to enhanced. Okara Fermenting requires Clean Enclosed Space.
Total score: 6/10 points		

He scored 10/10 for his OPM model, demonstrating a high level of attention to detail, model readability, and accuracy, as well as proficiency with concepts and terms associated with the system. Table 7 provides the analysis of his OPM model.

Although Eli got a full score for his model, based on his experience, building OPM models *"requires a lot of imagination and it's hard to attain this skill in such a short time."* When asked how the learning process benefitted him, he wrote that he has *"learned that any process can be described by a model,* [and that] *any process can be displayed by objects, sub-processes, and links. It will benefit me in the future when I try to learn or apply something new. Now that I know how to model any process, it will be easy to understand every subject."*

Eli's assignment related well to his OPM model. He used multiple representations, disciplines, and thinking skills, and skillfully integrated relevant sustainability and COVID-19 issues. As a result of the learning process, he reflected that *"the more processes I learned and the more ideas I was exposed to in the learning process, the more I was able to understand and develop the best assignment I could.* […] *The number of examples and the variety of questions gave* [me] *more possibilities both to understand things and later create things."* As for the relevance of the assignment, he stated that "*the more the topic related to me, the more I enjoyed it and the more willing I was to take on the challenge*." He also emphasized the importance of sustainability and COVID-19 to the relevance of the assignment, saying: *"I really enjoyed that there were things that concerned me and related to my world."*

Case 3—Danielle: Experienced economics and management and science teacher

Danielle has over 10 years of teaching experience, mostly with college students. She has a teaching certificate and also teaches

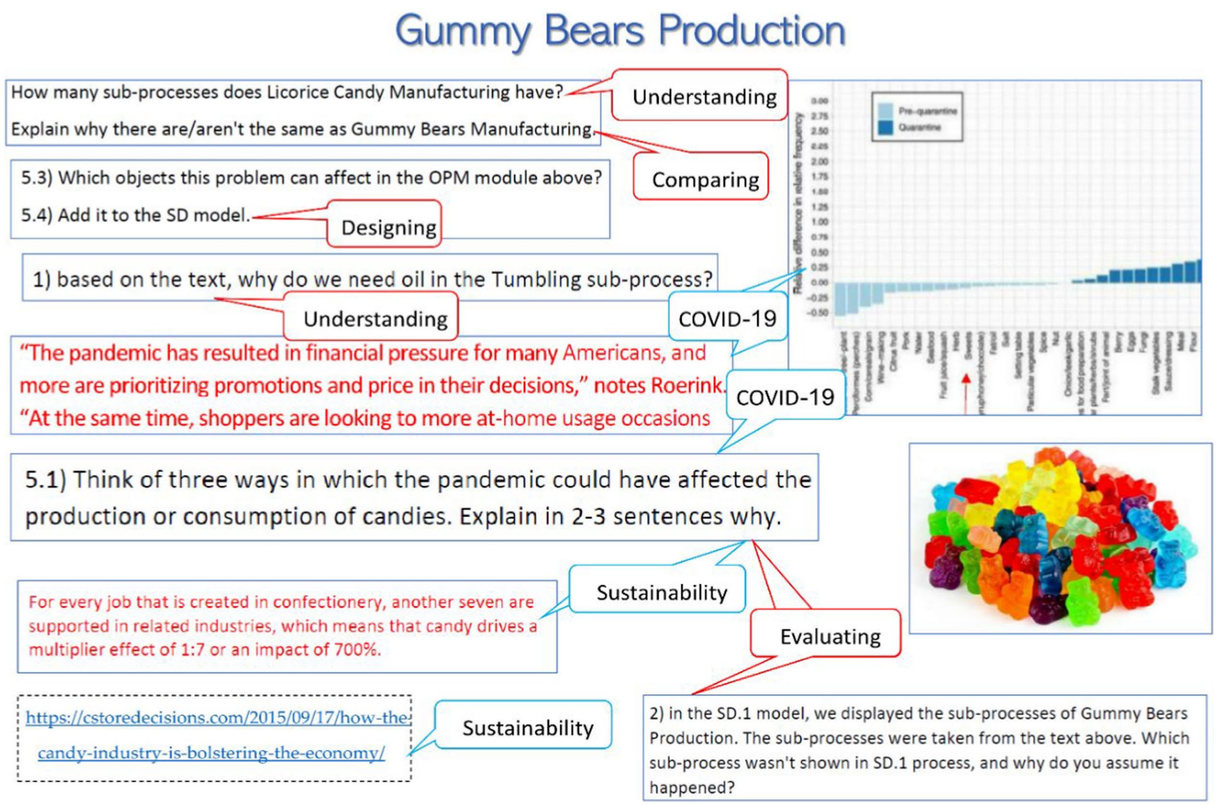


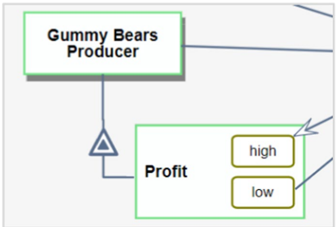
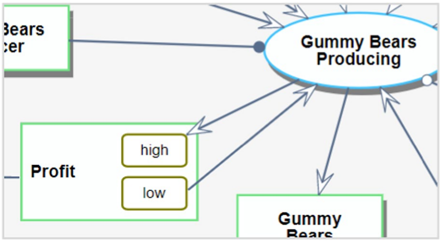
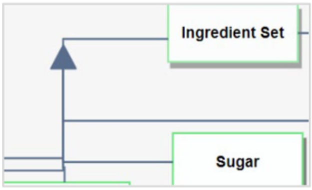
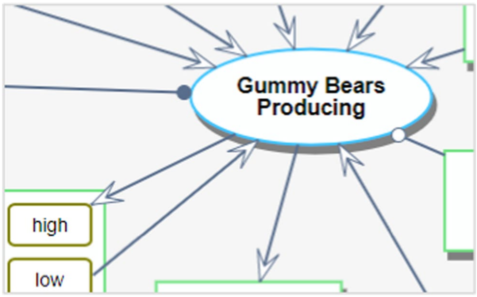
FIGURE 3
Selected segments from Eli's gummy bears production assignment.

science and technology in high school. She holds a PhD in economics and management, a field she teaches in colleges. It took her about 2 weeks to complete the learning process and about 3 weeks to develop her assignment. The food-related topic she chose was ice cream production, focusing almost exclusively on the engineering aspect. Selected sections of her assignment are shown in Figure 4, demonstrating that while she incorporated a variety of thinking skills, her assignment was at a low level. The model parts she used in her assignment were taken from her low-quality OPM model, which received a score of 4/10. For example, in the middle-upper area of Figure 4, a part of the model is missing. The disciplinary diversity was the lowest among the participants: only technology and environment were discussed.

Danielle had considerable difficulties during the learning process and in modeling as part of developing her assignment. She attended an online training delivered by one of the authors in the middle of the learning process, from which it emerged that she had specific difficulties internalizing the terms and ideas behind conceptual modeling and system concepts. Despite this training, no substantial improvement was evident from the modeling she performed during the learning process to the creation of the model for the assignment she developed. Indeed, she received a 4/10, the lowest score among the five participants. Her model lacked crucial parts: SD included only the main process without any linked objects, which was refined to SD1 with eight subprocesses, but not as a level by itself to provide abstract information about the system. Her SD1 was incomplete and inaccurate. The objects she included were only inanimate enablers, i.e., instruments, and human enablers, i.e., agents. As agent and instrument links indicate enablement rather than transformation, not a single subprocess in SD1 transformed an object. Object transformation is a key concept without which neither the purpose of a system can be described nor its behavior—the way the system changes over time. In her feedback, Danielle wrote that in developing her assignment *"the main difficulties were adapting my way of thinking to the model,"* and not, as might be expected, adapting the model to her way of thinking. She added that another difficulty in modeling was *"transitions between levels of analysis, combined with the interface* [i.e., OPCloud] *that was not so user-friendly for me."* It is worth noting that the rest of the participants expressed a positive opinion about the user-friendliness of OPCloud, and after the struggles of using it at first, they generally found it convenient.

Apart from the OPM model quality, which was rather low, her assignment was monotonous from both interdisciplinary and instructional points of view. Beyond the engineering aspect of ice cream production, the assignment included only an economic aspect. She referred to the effect of COVID-19 on the consumption of ice cream but did not include it in the model. Due to the low quality of her model, we do not present its analysis as done with the other cases.

TABLE 7 Scores and explanations for the OPM model created by Eli.

Attribute	Scoring and explanation	Examples in the model (screenshots)
A_1-Intended Purpose	3/3. The beneficiary, Gummy Bears Producer, is linked to the benefit, Profit at state high, via an exhibition-characterization link	
A_2-Main Function	2/2. The main process, Gummy Bears Producing, transforms (changes) the object Profit from state low to state high	
A3-Structural Relations	1/1. One whole-part link and two exhibition-characterization links were correctly used	
A4-Level of Complexity	1/1 Both SD and SD1 are included	n/a
A_5-Procedural relations	1/1. An instrument, agent, and effect link, and one Input-Output link pair. There were five consumption links, but there should have been only one such link, linked to a whole (Ingredient Set) and not to its parts	
A_6-Model readability	1/1. No points were taken off for misspellings in English	n/a
A_7-OPL main process procedural sentences	1/1. All three sentences are included	Gummy Bears Producing changes Profit of Gummy Bears Producer from low to high. Gummy Bears Producing requires Gummy Bears Production Equipment. Gummy Bears Producer handles Gummy Bears Producing.
Total score: 10/10 points		

Case 4—Ron: Physics high school and science middle school teacher

Ron is a high school physics teacher and a middle school science teacher with over 5 years of experience. His academic background includes a bachelor's degree in electrical engineering and a master's degree in science education with a teaching certificate. Relative to other participants, developing the assignment took him a lot of time, about three and a half months after having completed the learning process, which took him about a month.

The assignment he developed was framed by sustainability in the context of using writing paper. As he explained, developing a complex assignment like this requires a topic that he is passionate about, not just one he is familiar with or even knowledgeable about. We approved his selection because the topic he chose is complex enough to form a basis for the OPM model and because it relates to sustainability, an aspect that had to be incorporated into the assignment. Segments from his assignment are shown in Figure 5, where Hebrew parts are translated in red. Particularly prominent in his assignment and evident in Figure 5 is the monotony of the variety of thinking skills:

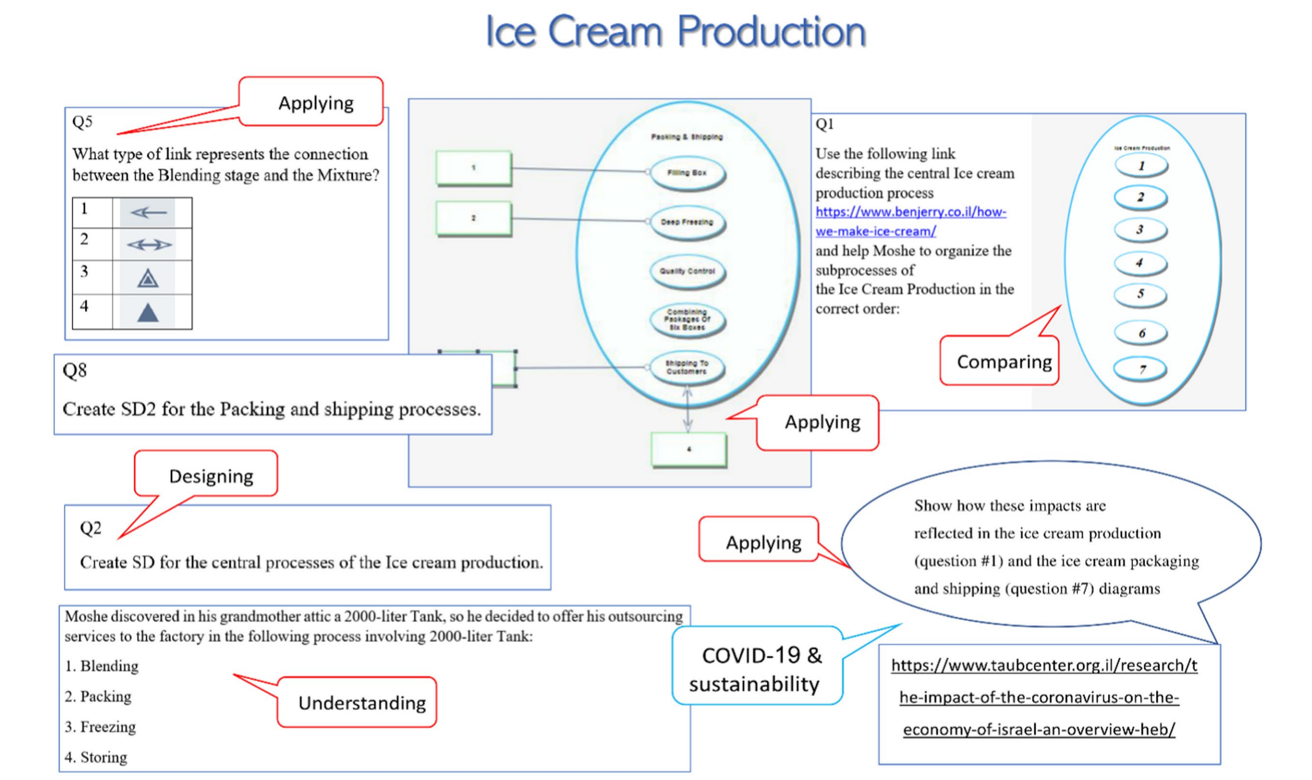


FIGURE 4
Selected segments from Danielle's ice cream production assignment.

the potential student needs only a basic understanding level to complete the assignment. Consequently, he received the lowest score for the variety of thinking skills attribute (see Analysis of the developed assignments). Additionally, he was the only one who did not include any part of his OPM model in the assignment.

The main process in SD of the OPM model Ron created included Paper Recycling, which is refined in SD1 into eight subprocesses. His model received 7/10, with three points deducted for not attaching the model's OPL and not defining the beneficiary (Table 8). The model, both SD and SD1, was created in Hebrew, his mother tongue, rather than English, as in the other cases. He explained that he could have done it in English, but the attention to detail would not be the same for him in this case. Reflecting on the modeling side of the learning process, he stated: *At first, I had the feeling that conceptual modeling is limiting because it puts every occurrence and data into a model of processes and objects. After practice and work, I reached a high level of thinking thanks to the organized structure of the modeling, and thus actually developed thinking processes at a very high level. For me, this is reflected in the instructional aspects of the assignment planning and not only in the modeling requirements* [throughout the learning process].

Regarding the assignment development, he explained that it took him considerable time to understand how to include in the model educational aspects, not just technical ones. As he explained, the assignment he developed is part of a lesson plan on misconceptions about recycling and sustainability that he had been contemplating for several years. He emphasized the difficulty in translating the already crystalized educational idea into a learning unit based on modeling and systems concepts. Working with OPM, he added, *"helped me understand what the appropriate goals for the lesson plan are for 10th graders, and how to apply them."* The main effect that the learning process had on the development of the assignment for him is the gradual increase in the level of difficulty, and accordingly, the construction of the system and modeling ideas that focus on the details first and eventually converge into a complete model.

Case 5—Romy: A novice technology college teacher

Romy holds a bachelor's degree in industrial engineering and management and textile engineering. In addition, she has a PhD in science and technology education and a teaching certificate in computer science. Her teaching experience includes about 2 years as a teaching assistant and lecturer in teacher training and development programs, and about a year as a teacher at a technology college. It took her about 2 days, much faster than the other participants, to complete the learning process, and another month to develop her assignment. The assignment revolved around the bread making process, from making the dough to packaging the bread for distribution. It began with a video of the entire process, which was followed by a list of 13 steps it includes. Figure 6 shows selected sections of her assignment, strongly highlighting the variety of visual representations that she included in the assignment. The high level of the other attributes is also evident in the variety of thinking skills, the variety of aspects and disciplines, and a successful combination of sustainability and COVID-19 in the context chosen for the assignment.

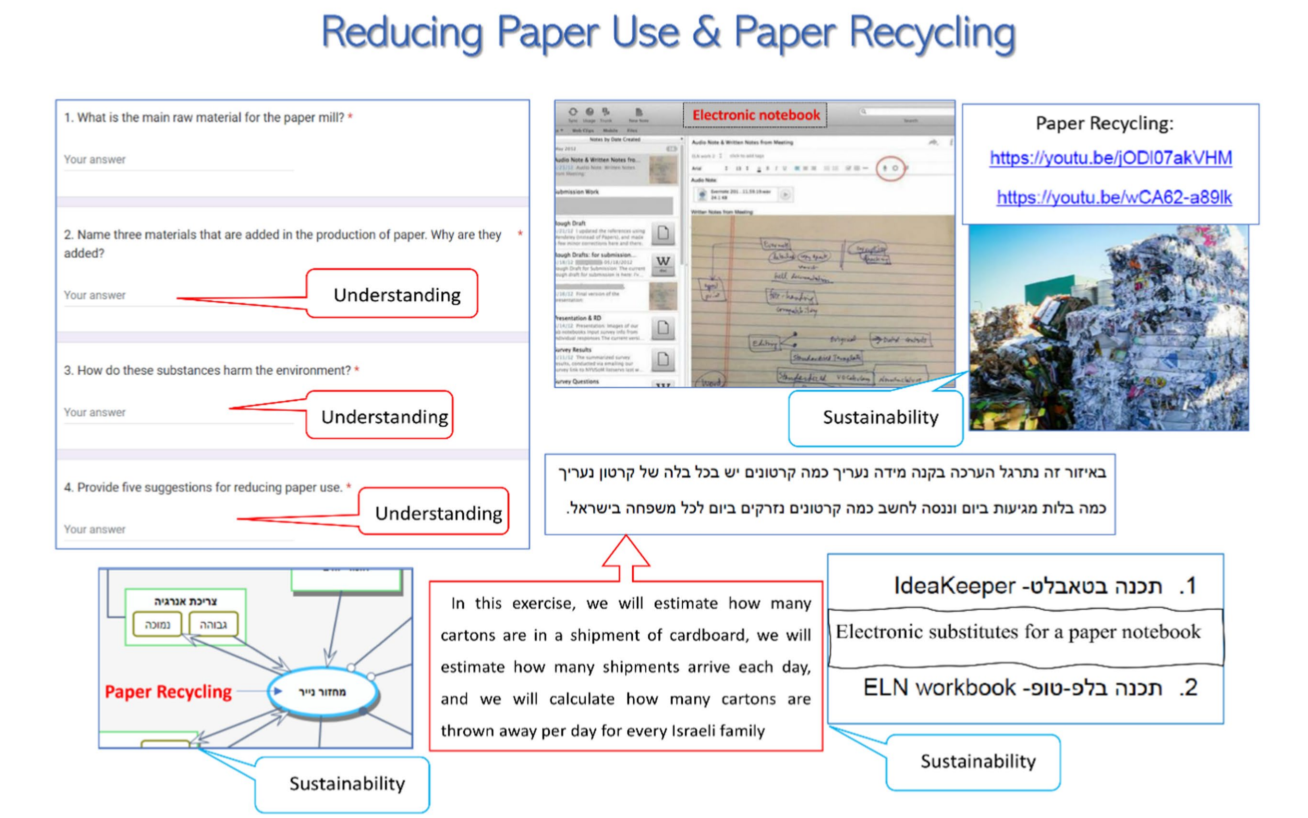


FIGURE 5
Selected segments from Ron's paper recycling assignment. The left-bottom part was not included in the assignment, but it appears in an appendix along with his model.

The main process of the OPM model she designed was Bread Baking and Packing, a model that clearly described each step included in the assignment. The scoring of her OPM model is explained in Table 9. She gained the biggest improvement in modeling from the level of the models she created during the learning process to the level of the model she created in the assignment she developed. She wrote that *"The difficulties increased as the lessons continued. In the beginning, it was not difficult at all, but in the end, it was very difficult."* Unlike most of the participants, at the beginning of the learning process she did not encounter the difficulty that others encountered as they needed to acquire a new language and new concepts. However, she thought that *"in using* [and learning] *the OPM, I think more practice is required, starting with simpler systems."* In addition, she *"felt that more advanced concepts were missing, and with more learning time this would also be possible, in addition to imparting the basic concepts in a more sustainable way."*

Analysis of the developed assignments

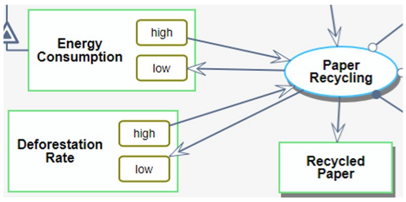
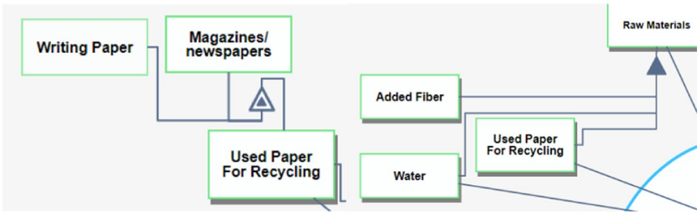
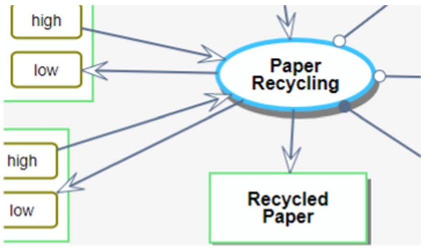
Once participants achieved basic systems thinking and conceptual modeling skills, they could seemingly begin to develop an assignment based on system concepts and conceptual modeling. However, the level that was sufficient to create conceptual diagrams according to specified guidelines may not be sufficient to independently create a complete model from scratch.

We wanted to test their ability to integrate conceptual models and system concepts into context-based learning rather than teach isolated facts. We also wanted to test their ability to combine in their assignment different thinking skills, information representations, and aspects of the topic they chose. Following the rubric for the assignments presented in the Materials and Methods section, we start with presenting the assessment charts of each of the five assignment cases. A common and effective way to present a qualitative assessment of learning and skills is spider charts, also known as radar charts, as shown in Figure 7. Explanations for the scoring of the six attributes for each chart are presented in Table 10. The assignment development process of the five participants is described qualitatively in the previous section. In this section, we present quantitatively the weaknesses and strengths of each participant for each of the six attributes. At the same time, both in the spider charts (Figure 7) and in Table 10, the performance of all five participants is presented along each attribute. This section thus complements the previous one, expanding on insights derived from the results.

Discussion

This study describes a new online learning process based on conceptual models, system basics, and food contexts, at the end of which participants are required to develop an assignment for their current or future students based on conceptual models in the spirit of

TABLE 8 Scores and explanations for the OPM model created by Ron.

Attribute	Scoring and explanation	Examples in the model (screenshots)
A_1-Intended Purpose	1/3. A beneficiary is missing. One agent is included, Factory Workers*, but workers generally do not directly derive value and benefits from the system but get paid by its beneficiary. The benefit, from the recycling plant's point of view, is Recycled Paper	
A_2-Main Function	2/2. The main process, Paper Recycling, transforms (changes) two objects, Energy Consumption and Deforestation Rate**, and yields Recycled Paper	
A_3-Structural Relations	1/1. One whole-part link was correctly used (right side). Two exhibition-characterization links were used, one of them incorrectly (left side)	
A_4-Level of Complexity	1/1. Both SD and SD1 are included	n/a
A_5-Procedural relations	1/1. Two input-output link-pairs. Two instrument links and one agent link. One consumption and one result link	
A_6-Model readability	1/1. The SD1 has several links that cross each other, but most of the model is readable and clear	n/a
A_7- OPL main process procedural sentences	0/1. OPL is not attached	n/a
Total score: 7/10 points		

*According to the Singular Name OPM Principle, plurals have to be converted to singulars by adding the word "Set" for inanimate things or "Group" for humans. Therefore, it should have been Factory Worker Group and not as modeled.

**Environmental objects and processes in OPM are represented by a dashed line, as opposed to a solid line representing systemic processes. In this case, both Energy Consumption and Deforestation Rate should have been modeled with dashed lines, but no points were deducted for that matter.

the learning process they had gone through. Once the fundamentals have been acquired through the learning process, they had the needed content knowledge to develop their assignments. In analyzing the five assignment cases included in the study, we assessed the participants' performance in two aspects: (1) conceptual modeling and systems thinking, and (2) integration of conceptual models, systems thinking, visual representations, and interdisciplinarity, as well as sustainability and COVID-19 topics into their assignments.

The study adopted the collective case study approach, combining qualitative and quantitative methods aimed to discover new insights. In the next sections, we respond to the two research questions. The first question deals with the way STEM teachers cope with online learning of conceptual modeling and systems thinking in the context of food production and sustainability. The second question focuses on these teachers' online assignments that they developed for their students. This RQ is addressed in the last section of the Discussion: "Teachers' conceptual modeling and system concepts knowledge while developing learning materials."

Conceptual modeling and systems thinking competence of STEM teachers

Most of our participants with an educational background who performed the online learning process we had developed did not have a background in conceptual modeling and systems thinking. Regardless of their teaching experience, none of the five assignment case authors selected for this study had a relevant background, and

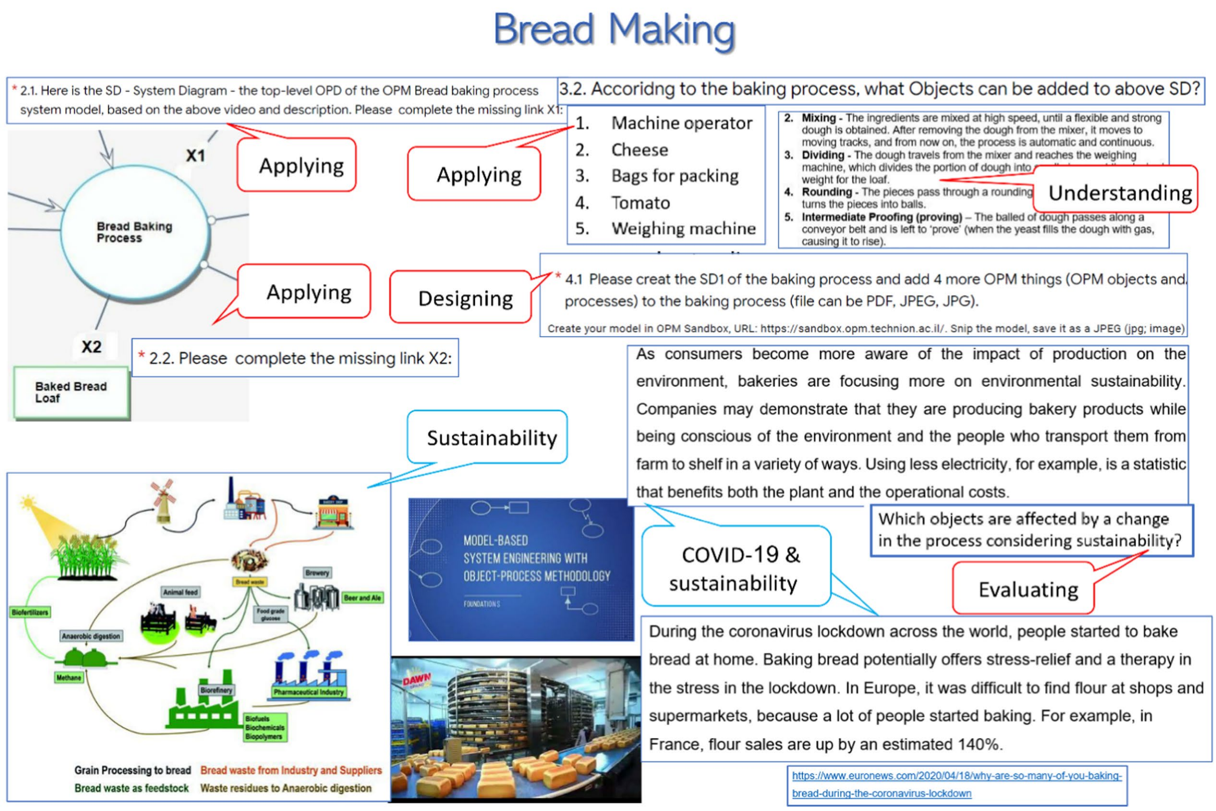


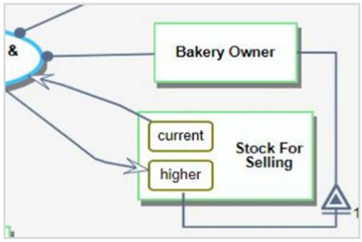
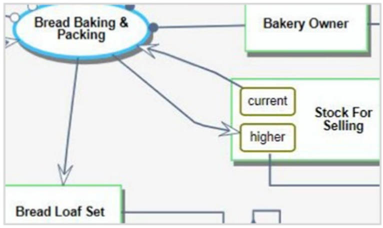
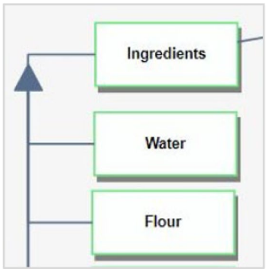
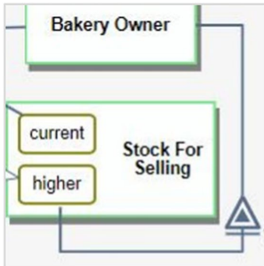
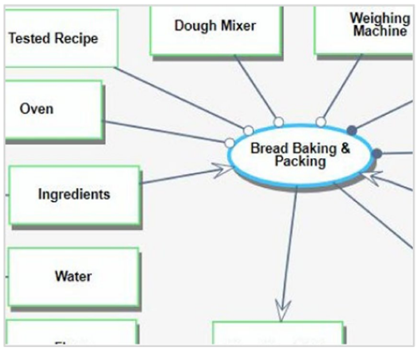
FIGURE 6
Selected segments from Romy's bread making assignment.

therefore it would not be unreasonable to infer that the knowledge and skills with which the participants began to develop their assignment were acquired as a result of the learning process they had previously completed. During the learning process, participants gained varying levels of knowledge and understanding of conceptual modeling and systems thinking. For most of them, this was the first introduction to these concepts, as evidenced by their reflections.

Explicit teaching of systems thinking: Using ontological scaffolding

Talanquer (2019) presented a year-long systems thinking-oriented undergraduate general chemistry pilot course. As a result of the course, students were reportedly able to identify processes, interactions, and components in given systems, and also to produce related explanations and build arguments, but only after significant scaffolding and prodding. Our objective was to get educators acquainted with system fundamentals, such as function, structure, behavior, and purpose, by using conceptual modeling in OPM and using them to compose assignments for their current or future students. To this end, we provided the learners with an ontological framework that involved teaching system concepts and modeling them in context. This is in line with other studies, such as those of Verhoeff et al. (2008), Yoon (2008), Yoon et al. (2018), and Rates et al. (2022), who emphasized the importance of explicitly instructed ontological knowledge regarding system concepts and ideas. Engaging in conceptual modeling activities before and during the assignment development was the practical part of the participants' learning process. This became possible after participants had acquired the ontological foundations of OPM that enabled them to start engaging in OPM-based conceptual modeling. We agree with Rates et al. (2022), who argued that complex systems can easily be misunderstood and misconceptualized when learners have wrong ontologies. As we saw, at the beginning of the learning process, teachers often lack basic systems-related ontological knowledge. This may significantly impede learning that is based on systems thinking, and even more so when such knowledge has to be combined with assessment knowledge, as was the case in our study. One participant, Danielle, who failed to achieve mastery of basic system concepts, experienced major difficulties throughout the entire process, especially in developing her assignment. Arnold and Wade (2017) also argued that while ontological scaffolding is indeed important (e.g., Jacobson et al., 2011; Rates et al., 2022), the inclusion of overly complex system terms and concepts may withhold their instillation among educators. Arnold and Wade (2017) called for a more approachable language for those lacking profound systems knowledge, one accessible outside the systems community. We agree with this because we believe that making systems thinking and conceptual modeling accessible calls for combining different approaches: primarily an explicit systems ontology (e.g., Rates et al., 2022), against the background of treating systems thinking as a cognitive skill like any other skill, which is not reserved only for the systems community (Chowdhury, 2023).

TABLE 9 Scores and explanations for the OPM model created by Romy.

Attribute	Scoring and explanation	Examples in the model (screenshots)
A1-Intended Purpose	3/3. The beneficiary Bakery Owner is linked to the benefit, Stock For Selling at state higher	
A2-Main Function	2/2. The main process, Bread Baking and Packing, transforms (in this case, changes and yields, respectively) the objects Stock For Selling and Bread Loaf Set	
A3-Structural Relations	1/1. Two link types were used: a whole-part link (Left figure), and an exhibition-characterization link (Right figure)	 
A4-Level of Complexity	1/1. Both SD and SD1 are included	n/a
A5-Procedural relations	1/1. Input-Output link-pair, consumption link, result link, instrument links, and agent links	
A6-Model readability	1/1	n/a
A7-OPL main process procedural sentences	0/1. OPL is not attached	n/a
Total score: 9/10 points		

Systemic knowledge acquisition versus systemic knowledge application

Based on our findings, we view the conceptualization of Arnold and Wade (2017), *gaining systemic insight* vs. *using systemic insight*, as an appropriate description of the learning process we have developed and implemented. First, the participants acquired basic knowledge that allowed them to *gain* systemic understanding and communicate the knowledge acquired in systems science language. Then, as the scaffoldings were gradually removed, they could *use* this knowledge to create models on their own as a central artifact of their self-developed student assignments. As reflected in the last learning module score, most of the participants gained a sufficient level of modeling and proficiency in system concepts that enabled them to develop the assignments.

Modeling engineered systems in combination with natural phenomena

Only one assignment—paper recycling—involved a model that focused on an engineered system with environmental, natural objects undergoing a transformation—deforestation and energy consumption. The low level of integration of natural

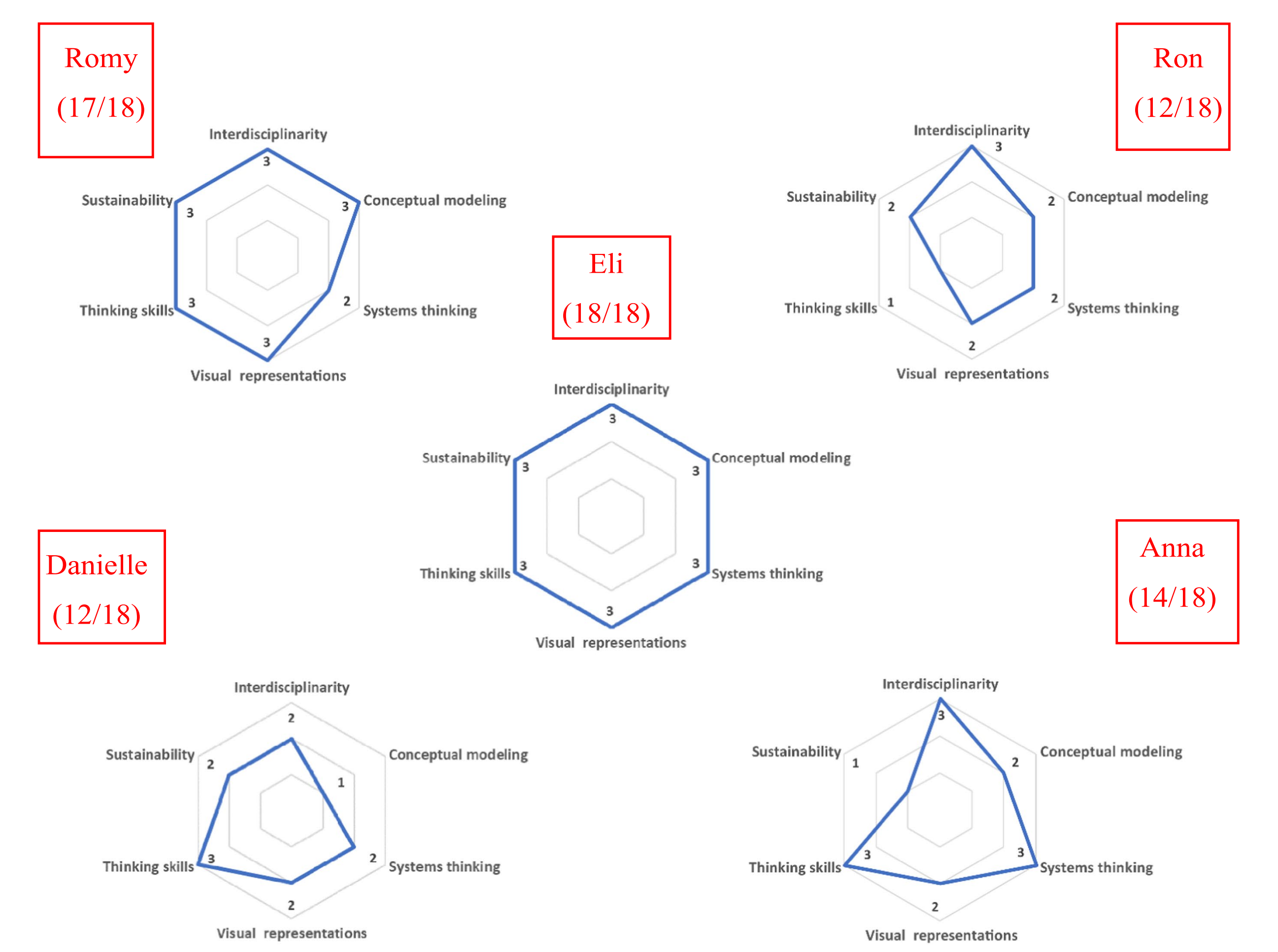


FIGURE 7
Spider charts of the five teacher assignments showing for each teacher the total score and scores of each of the six attributes.

aspects into human-made engineered systems in the participants' assignments despite the instruction to include a sustainability aspect in the assignment content calls for further research to understand why this posed a challenge and how such integration can be fostered.

Teachers' conceptual modeling and system concepts knowledge while developing learning materials

Developing assignments based on conceptual models presented the participating teachers with a complex task. This complexity was reflected throughout the process in two main aspects. First, the need to create models from scratch to represent their system of choice required a significant leap from the learning process, where the modeling requirements were more structured. Second, the participants had to combine instructional knowledge, assessment knowledge, content knowledge, and systems and modeling principles into a coherent, thought-provoking, and cohesive assignment. The focus shifted from teachers acquiring systems thinking and modeling content knowledge in the learning process to practicing creativity in composing assignments that we strive to endow them with so they apply it in their educational work. Indeed, teachers often need to combine principles from different fields to reach quality learning materials. We thus join the recommendations for meaningful curricular integration of systems thinking and conceptual modeling in teacher training and professional development (e.g., Krell and Krüger, 2016; Rosenkränzer et al., 2017; Yoon et al., 2017). However, one aspect that has not been sufficiently researched and promoted is interdisciplinary domain-independent assessment knowledge-based teacher training and professional development. A number of researchers view assessment knowledge as a separate construct from PCK (e.g., Avargil et al., 2012; Tal et al., 2021). As a separate construct, assessment knowledge requires developed PCK as a prerequisite, so developing PCK may also directly or indirectly benefit assessment knowledge (Avargil et al., 2012). Therefore, assessment knowledge-focused training can better equip teachers with the necessary assessment knowledge and skills. Further research may clarify the differences between assessment knowledge-focused versus PCK-focused training in the context of complex systems and conceptual modeling. The learning modules we developed were designed to provide implicit guidelines to leverage instructional principles that make up both PCK and assessment knowledge. These guidelines can be used in follow-up studies.

TABLE 10 Assignment scoring explanations for all five cases, six attributes for each.

Participant attribute	Anna	Eli	Danielle	Ron	Romy
Conceptual modeling – OPM score	6/10 – Intermediate-2	10/10 – High- 3	4/10 – Low-1	7/10 – Intermediate-2	9/10 – High-3
Systems thinking mean score for the learning process	8/10 – High- 3	8.8/10 – High-3	6.4/10 – Intermediate-2	7.8/10 – Intermediate-2	6.6/10 – Intermediate-2
Visual representations variety	Three representations: Text, diagrams, and links – Intermediate-2	Five representations: Photos, diagrams, figures, text, and links – High-3	Four representations: Text, diagrams, tables, and links – Intermediate-2	Three representations: Text, photos, and links – Intermediate-2	Six representations: Text, diagrams, photos, figures, videos, and links – High-3
Thinking skills variety	Four thinking skills: Understanding, applying, comparing, and designing – High-3	Four thinking skills: Understanding, comparing, evaluating, and designing – High-3	Four thinking skills: Understanding, applying, comparing, and designing – High-3	One thinking skill: Understanding – Low-1	Four thinking skills: Understanding, applying, evaluating, and designing – High-3
Sustainability and COVID-19	Indirect reference to sustainability. The COVID-19 aspect was not relevant to tofu production – Low-1	Both sustainability and COVID-19 were integrated and relevant to the assignment: The economic, social, and behavioral effects of COVID-19. Socio-economic effects related to the confectionery industry – High-3	Both are included, but their relevance and integration could have been better – Intermediate-2	Most, if not all, of the assignment, deals with sustainability, but with no reference to COVID-19 at all – Intermediate-2	Both sustainability and COVID-19 were integrated and relevant to the assignment: The impact of environmental awareness and COVID-19 lockdowns on bread consumption habits – High-3
Interdisciplinarity: number of involved disciplines or aspects	Three aspects: economic, food engineering, and scientific – High-3	Four aspects: economic, social, technological, and economic – High-3	Two aspects: Technological and environmental – Intermediate-2	Four aspects: environmental, physical, technological, and economic aspects – High-3	Four aspects: Economic technological, environmental, and social – High-3
Total: (out of 18)	14	18	12	12	17

Conclusion

The cases described and analyzed qualitatively and quantitatively in this paper indicate that the learning process presented in this study may significantly benefit teaching complex phenomena and processes in STEM disciplines. Teachers' engagement in learning complex systems basics in conjunction with conceptual modeling can be facilitated by putting them in the context of real-life complex phenomena that are relevant to the learner. Based on the desired learning outcomes, teachers can apply systems thinking and modeling methods and techniques they had acquired in their professional development to teach system principles and explain complex phenomena. Adequate accessible modeling methods and tools, such as OPM on the OPCloud platform, are key to endowing teachers and later their students with systems and modeling concepts whose abstract nature is alleviated by grounding them to concrete visual models that are interpreted textually on the fly.

The rubric enabled tracking different levels of assessment knowledge through six different attributes, but additional quantitative research is needed to further validate this conclusion. This rubric can be used to assess a large number of participants in teacher training and professional development programs, not only for summative assessment but also for formative one, as argued by Panadero and Jonsson (2020). The rubric provides for monitoring learners' progress during task performance to identify individual strengths and weaknesses. Formative assessment is of paramount importance in context-based learning professional development programs for teachers (Pilot and Bulte, 2006). The spider charts can also be applied as part of formative assessment for tracking the learning process, not just for summative assessment and not only for research purposes but also for educational assessment in practice (Kaczynski et al., 2008).

Limitations and further research

The participants' perceptions, experiences, and contexts in the cases described in this article are described in detail, so other researchers can assess whether the conclusions arising from our findings can be applied to other circumstances, times, and frameworks. Yet, the low degree of generalizability that characterizes case studies calls for quantitative follow-up studies that would validate the findings on large samples.

The focus of this research was on human-made systems and processes, but science teachers are more into teaching natural systems and phenomena. This is especially true for biology, the field from which general systems theory emerged, as well as for chemistry and physics, where many complexities can be simplified by engaging in conceptual modeling. Being domain independent in its nature, OPM "opens system modelling to the entire scientific, commercial, and industrial community" (Dori, 2016, p. 376). That is, human-made and natural systems and phenomena alike can be modeled using OPM. Although OPM has been investigated in relation to natural sciences education (e.g., Lavi and Dori, 2019), it was almost exclusively for the purpose of assessing systems thinking and not for developing such thinking or for integrating it into educational content developed by the teachers themselves. The potential implications of this study may be extended through the inclusion of natural phenomena rather than or in addition to engineered systems in further studies.

Most of the participants in this study, as well as in previous studies that applied a learning process similar to the one described in this paper (e.g., Peretz et al., 2023), demonstrated the acquisition of adequate systems thinking and modeling foundations. However, more advanced concepts and ideas such as feedback loops and conditional links are very relevant to many topics that science teachers are expected to teach. Since the completion of the current research, we have developed three additional modules that have been added to the learning process, containing more advanced approaches to systems engineering with OPM, such as decision nodes, conditional links, feedback loops, and logical operators. Future research should examine how educators without a relevant background cope with similar but more advanced learning and assignment development processes. Including the advanced modules is expected to expose the full potential of this learning process, and consequently, improve teachers' and students' modeling and understanding of complex systems. Being a formal conceptual modeling methodology and language, OPM includes recognized, unambiguous definitions of key system principles and their modeling. Further research will be needed to determine if OPM can be used to develop advanced systems thinking among teachers, similar to the process that has been taking place in systems engineering courses at the Technion.

With the exception of one, the models created by the participants in their self-developed assignments were significantly more elaborate and extensive than those created during their learning process, where they did not get to choose the domain and context of their interest. Further quantitative research is needed to determine if this finding can be generalized, and if so, what is the strength of the relationship between the quality of the model and the relevance of the chosen topic.

Finally, a follow-up study on the participants who completed the learning and development processes at a future point in time will provide a longitudinal view of the extent to which systems thinking and conceptual modeling skills developed by the participants are retained over time.

Contributions

This study integrates systems thinking and conceptual modeling skills, sustainability, interdisciplinary thinking, instructional knowledge, and assessment knowledge into student assignments developed by educators. This unique combination has provided for monitoring and documenting difficulties, challenges, and opportunities that arose in the process, opening the door for possible implementation in STEM education beyond research. The theoretical knowledge gained through this research can help to better design teacher training and professional development programs to cater to the growing need for systems thinking and modeling skills as emerging 21st century skills that teachers need to acquire and impart to their students. Knowing what to focus on in the development of teachers' knowledge and how to do it is a step towards a more competent education system that is ready for the changing, complex challenges we face in all areas of life. The study offers a methodological contribution by providing a basis for evaluating teachers' assessment knowledge and skills using the six-attribute rubric, subject to further validation in follow-up studies. After being established as a reliable and valid tool, this rubric will allow measuring progress in professional development and teacher training programs of a cross-disciplinary nature with activities focused on systems thinking and conceptual modeling in diverse contexts. As reflected in some of the cases in the research, modeling and systems thinking not only helped in gaining content knowledge and skills for teaching science, but also in structuring and contemplating teaching planning. This is an interesting aspect that we did not expect before starting the research, and establishing it may provide important added value to our research and science education research in general.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving human participants were reviewed and approved by the Behavioral Sciences Research Ethics Committee of the Technion—Israel Institute of Technology. Approval number 2020–165. The participants provided their online informed consent to participate in this study.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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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.

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*CORRESPONDENCE
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✉ production.office@frontiersin.org

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Due to a production error in Table 3, the "Content description" column heading was placed above the "Module" column, and vice versa. This has been rectified.

In the published article, there was an error in the **Abstract**. The original sentence was: "Research tools included the online assignment that the participants developed, dedicated rubrics for analyzing their assignments, accounting for use of modeling, media, visualization, micro–macro-process scientific understanding levels, and a mix of closed- and open-ended questions."

This should have been written as: "Research tools included the online assignment that the participants developed, a dedicated rubric for analyzing their assignments, accounting for use of modeling and systems concepts and the integration of sustainability and COVID-19 issues, a variety of thinking skills, visualizations and disciplines, and a mix of closed- and open-ended questions."

The publisher apologizes for these errors. The original article has been updated.

TABLE 3 The content of the four modules that formed the learning process.

Module	Content description
1	- Introduction to OPM. - Identifying objects, processes, and states in a system.
2	- System aspects: function, structure, and behavior. - Structural relations, state transitions, system aspects, and OPM modalities.
3	Understanding the System Diagram (SD): System Purpose—beneficiary and benefit, system function; and process enablers—agents and instruments.
4	- Diving into the details: the first detail level (SD1) of the OPM system diagram, divided into major subprocesses. - Synchronous vs. asynchronous processes.

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André Bresges,
University of Cologne, Germany

REVIEWED BY
Alfonso Garcia De La Vega,
Autonomous University of Madrid, Spain
Cristal Schult,
University of Cologne, Germany

*CORRESPONDENCE
Ram Tamir
✉ ramtam@post.bgu.ac.il

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System-thinking progress in engineering programs: A case for broadening the roles of students

Ram Tamir[1]*, Orit Ben-Zvi Assaraf[1] and Shimrit Maman[2]

[1]School of Education, Ben-Gurion University of the Negev, Beer-Sheva, Israel, [2]Homeland Security Institute, Ben-Gurion University of the Negev, Beer-Sheva, Israel

Introduction: Complex systems are prevalent in many scientific and engineering disciplines, which makes system thinking important for students of these fields. Duchifat 3 is a unique engineering educational extracurricular program, where high school students designed, assembled, and tested a nano-satellite.

Methods: This study applied qualitative methods to explore how the participants' systems-thinking developed during the program. Participants were interviewed using the repertory grid interview, and a semi structured interview at the beginning and at the end of the project, while various observations were conducted throughout.

Results: While the participants were initially assigned narrow roles, each dealing with a single sub-system of the satellite, some chose to be involved with other sub-systems and aspects of the project. Our findings show that the broader the participants' involvement was, the greater the progress they experienced in their systems-thinking. Participants who stayed focused on a single subsystem did not show progress, while participants who involved themselves with several sub-systems exhibited a more meaningful progress.

Discussion: Although the program design aimed to assign students to a narrow role to enable them to achieve the educational goals, from the perspective of systems-thinking this was counterproductive. These findings shed light on the design of engineering programs such as the one examined here in terms of systems-thinking development. We discuss the implications of the findings for similar programs and make suggestions for improvement.

KEYWORDS

systems-thinking, project-based learning, case study, repertory grid, CubeSats

Introduction

Trends in science education have emphasized the integration of core ideas and crosscutting concepts in STEM subjects—including the complex systems ideas that comprise systems thinking (NGSS Lead States, 2013). Complex systems are prevalent in many scientific and engineering fields, and at all scales—from the micro-scale of a single cell to complex macro systems such as cities or ecosystems (Yoon et al., 2017). The ability to understand the whole system and see the big picture, understand interconnections, understand synergies, and understand the system from multiple perspectives is one of the cognitive characteristics required of successful systems professionals (Frank, 2010). Although research in engineering system thinking is somewhat limited, it is becoming ever more important as engineering systems become more complex (Greene and Papalambros, 2016).

This study examines a specially designed engineering extracurricular program, in which high school students participated in the task of assembling a nanosatellite, Duchifat 3, which was launched into orbit in 2019 and was functional in space for about a year. The program involved the use of STEM content, and is part of a series of projects where high school students engage in the task of engineering, integrating and testing CubeSat satellites (Brosch et al., 2017; Millan et al., 2019). Although there are a number of programs that introduce satellite design into high schools (Millan et al., 2019), to the best of our knowledge, this is the first in-depth study of such an educational program. In this paper, we analyze the development of the participants' systems thinking, describing the progress the participants made and offering insights into what may encourage such progress in terms of program design.

Background

Systems thinking

Systems thinking is a way to understand, explain, and interpret complex and dynamic systems. A complex system is composed of various elements that interact *via* simple local rules (Fuentes, 2014) and give rise to certain functions (Gilissen et al., 2020). Interactions are characterized by feedback loops and are usually nonlinear (Fuentes, 2014; Yoon et al., 2018). Complex systems have a hierarchical structure, with multiple components that interact dynamically, nonlinearly, and simultaneously, within or across levels. Such interactions, moreover, are often implicit, occurring over time, at varying microscopic and macroscopic levels, and with indirect causality that is difficult for students to trace and grasp (Hmelo-Silver and Azevedo, 2006; Schneeweiß and Gropengießer, 2019). Systems thinking is a set of skills that can be taught separately, and a learning strategy that explicitly considers system characteristics in trying to understand and predict natural phenomena and complex man-made systems (Verhoeff et al., 2018).

There are several conceptualizations of systems thinking skills in the literature. Table 1 maps these conceptualizations, highlighting their common themes. Though not a comprehensive or exhaustive review of the literature, the table features those works in the field that are most prominent and relevant to this study. As this table shows, a proficient systems thinker must identify the systems' components and their interrelations, consider the system and its subsystems at various scales and levels of organization, identify and describe feedback loops that may control processes in the system, identify the dynamic relationships and consider the temporal dynamics of the system, make generalizations and predictions in regard to the system, and identify emergent properties and understand decentralized control.

Fostering systems thinking

Several strategies for fostering systems thinking have emerged from the literature. Our study focused on the three most prominent, as identified by Gilissen et al. (2021): (1) Modeling; (2) Cross-level reasoning; and (3) Use of systems language.

Modeling

Models are representations of natural phenomenon, data, theory, or of engineered manmade objects and processes. They may consist of 3D or 2D representations, and they may be verbal, mathematical, or computational. Models represent a subset of the parts of the modeled entity depending on its purposes. (Krell et al., 2019). Modeling can help students better understand the dynamics of a system and integrate knowledge about it (Wilson et al., 2020). Its use in education consists of two central parts: models that communicate scientific or engineering content *to* students and modeling done *by* students to gain insight (Upmeier zu Belzen et al., 2019). In the latter case, modeling is instrumental in making students' understanding visible, helping students organize their ideas, and facilitating constructive and collaborative discussion (Hmelo-silver et al., 2017; Bielik et al., 2021). It allows students to engage in inquiry practices by gathering data, generating hypotheses, and testing them (Hmelo-Silver et al., 2015).

Cross level reasoning

Weintrop et al. (2016) identify cross-level reasoning (thinking across levels in their terms) as core to systems thinking. Systems can be understood by analyzing different levels of organization from the micro scale to the macro scale. Different insights can be gained from examining different levels which can lead to a better understanding of the emergent characteristics of the system as a whole (Weintrop et al., 2016). Challenging students to reason between various levels of organization has been shown to improve system thinking (Verhoeff et al., 2008; Gilissen et al., 2021).

Systems language

Systems language is the explicit use of terms that refer to system characteristics. Proponents of this strategy contend that when teaching about complex systems and encouraging system thinking, teachers should make explicit use of systems language and encourage their students to use that language explicitly (Eberbach et al., 2021). Deconstructing a phenomenon to its characteristics and discussing them explicitly has been shown to help clarify it for both students and teachers (Zion and Klein, 2015). Jordan et al. (2013) showed that exposure to the systems language helps students in their explanations by linking multiple ideas and improving their explanations' sophistication by enriching references to invisible elements. Nguyen and Santagata (2021) have shown that the teacher's prompts greatly affect how middle school students respond when asked about connections in systems. The language teacher's use is adopted by students, not only in their discussions with the teacher but also in their group discussions without the immediate presence of the teacher, thus assisting their understanding of systems (Hmelo-silver et al., 2015). Systems language may help students to better communicate information about s system, which is also important for systems thinking according to Weintrop et al. (2016).

Evaluating students' conceptualization of complex phenomena

Several models have been put forth as useful means of representing the various forms and levels of system thinking. One promising approach is Structure-Behavior-Function (SBF) thinking (Hmelo-Silver et al., 2007). The "structure" in SBF models is represented in terms of the system's elements or components, the substances contained in the components, and connections among the components (Goel et al., 2009). "Behavior" refers to the mechanisms by which the structures perform their function, represented as a

TABLE 1 Mapping of different conceptualizations of systems thinking skills.

	Systems' elements and relationships	Cross-level reasoning	Feedback loops	Dynamic relationships	Temporal dynamics	Generalizations	Emergence
Arnold and Wade (2015)	Recognizing interconnections; understanding system structure	Understanding systems at different scales	Identifying and understanding feedback; differentiating types of stocks, flows, and variables	Identifying and understanding non-linear relationships; understanding dynamic behavior			
Ben-Zvi Assaraf and Orion (2005)	Identifying simple relationships between or among the system's components; organizing the systems' components, processes, and their interactions, within a framework of relationships	Recognizing hidden dimensions of the system—understanding natural phenomena through patterns and interrelationships not seen on the surface	Identifying cycles of matter and energy within the system—the cyclic nature of systems.	Identifying dynamic relationships within the system	Thinking temporally: retrospection and prediction; understanding that some of the presented interaction within the system took place in the past, while future events may be a result of present interactions	Making generalizations—solving problems based on understanding of systems' mechanisms; system-adequate intention to act	
Sweeney and Sterman (2000)			Discovering and representing feedback processes; identifying stock and flow relationships.	Identifying nonlinearities.	Considering time related dimensions.	Homologous reasoning—identifying similar underlying feedback structures in spite of different surface features; policy thinking	Understanding how the behavior of a system arises from the interaction of its agents over time
Evagorou et al. (2009)	Identifying the elements of a system; identifying influence of specific elements on other elements	Identifying subsystems within a system	Identifying feedback effects		Identifying temporal boundaries	Identifying the changes necessary for certain patterns to be observed	
Gero and Danino (2016)	Understanding the interrelations between the components and their synergies				Observing the system from a temporal viewpoint—examining the system's behavior as a function of time	Observing the system from a generic viewpoint—looking for similarity between the system and other systems; observing the system from an operational viewpoint—regarding the system as a black box	Seeing the system as a whole beyond its components
Gilissen et al. (2019)	Components that have interactions	Hierarchical nature of systems	Feedback loops, input and output	Dynamics			Emergence

(Continued)

TABLE 1 (Continued)

	Systems' elements and relationships	Cross-level reasoning	Feedback loops	Dynamic relationships	Temporal dynamics	Generalizations	Emergence
Hmelo-Silver and Pfeffer (2004)	Identifying behaviors and functions; connecting structures to behaviors and functions			Capturing the dynamic interdependencies		Focus on abstract processes and mechanisms	
Hmelo-Silver et al. (2017); Snapir et al. (2017)	Identifying and describing components in relation to mechanisms and behaviors	Identifying relationships between micro and macro				Identifying how phenomena are achieved	Identifying the overall behavior or property of the system that results from many interactions
Lavi and Dori (2019)	Identifying links between objects, links between process and links between objects and processes	Identifying number of detail levels and the refinement of diagrams into lower-level processes	Identifying different types of procedural sequences—linear, divergent, convergent and looping	Identifying different types of procedural sequences—linear, divergent, convergent, and looping		Identifying the intended purpose of the system, its main function and main process; identifying the object transformed by main process and its parts	
Mambrey et al. (2020)	Complex system organization		Complex causality				
Mehren et al. (2018)	Identifying networked elements and relationships		Identifying feedback loops	Identifying linear and nonlinear dynamics	Consideration of systems dynamics	Making prognoses based on direct and indirect effects; consider regulative measures based on complex effect analysis	Identifying emergent characteristics
Samon and Levy (2020)				Local dynamic processes, which result in the system; approaching equilibrium. These processes continue after reaching equilibrium			The whole is more than the sum of its parts; Decentralized control, the macrophenomenon results from random actions, and interactions at the micro-level

sequence of states and transitions between these states. Explanations for state transitions may include scientific laws, functions of the subsystems, structural constraints, or other behaviors (Hmelo-Silver et al., 2007; Goel et al., 2009). "Function" refers to the role or the purpose of elements in the system. A function is represented as a schema containing a reference to the behavior that accomplishes the function (Hmelo-Silver et al., 2007; Goel et al., 2009). Hmelo-Silver et al. (2017) modified the SBF model, creating an alternative conceptual framework called Components-Mechanisms-Phenomena (CMP). This framework provides a representation of all the system's attributes, including the structures (components) within the system, the specific processes and interactions (mechanisms) that occur between them, and the macro scale of processes and patterns within a system—the phenomena.

In addition to providing a vocabulary for discussing complex systems, these frameworks also serve as a means of externalizing and assessing the development of students' systems thinking. Thus, for instance, when explaining complex systems within the CMP framework, referring to phenomena and mechanisms indicates more advanced systems thinking than referring to components (Hmelo-Silver et al., 2017; Snapir et al., 2017).

Assessing traditional learning is often challenging enough, but modern notions of science teaching, such as system thinking, require creative assessment designs. One tool that has been used on multiple occasions as a means of assessing systems thinking is Kelly's repertory grid (RG) technique, which explores learners' perceptions through the personal constructs they create. The technique is based on Kelly's theory of personal constructs, which states that the world is perceived in terms of the meaning people apply to it (Kelly, 1955). According to this theory, people make sense of the world by viewing reality through personal constructs. These allow them to make predictions about the future, which are later tested against reality and reformulated in an iterative process (Jankowicz, 2001). As a person experiences repeated events, he or she starts to make sense of them, identifying similarities and differences between events, and separating them based on constructs (Rozenszajn et al., 2021). As a result, one's personality, attitudes, and concepts are developed on a system of personal constructs which are tacit in nature.

Kelly developed a methodology for exploring these systems of personal constructs with repertory grids (RG). This technique is a form of highly structured interview, designed to assign relationships to personal constructs and given objects of discourse (Kelly, 1955). The repertory grid technique has been acknowledged for several decades as a reliable way to represent how learners think and help them represent their mental models explicitly (Bezzi, 1999; Ben-Zvi Assaraf and Orion, 2010; Rozenszajn and Yarden, 2015; Snapir et al., 2017; Wu et al., 2018). Previous studies have demonstrated the strength and validity of the RG as an effective tool for assessing learners' conceptual models, providing valuable insights into the learning process, and identifying problems in understanding biological concepts (McCloughlin, 2017). Several studies have demonstrated the added value of the technique for assessing students' conceptual models and system thinking abilities in the context of ecology (Keynan et al., 2014), biogeochemical cycles (Ben-Zvi Assaraf and Orion, 2010), and human body complexity (Ben Zvi Assaraf et al., 2013; Snapir et al., 2017).

Research question

This paper presents part of a larger study that examined the Duchifat 3 extracurricular project, in which high school students were involved in designing, building, and testing a nano-satellite. It addresses the following question:

> What aspects of systems thinking were exhibited by the participants and how did their systems-thinking progress during the program?

Methods

Methodological foundation

This study is based on the qualitative research paradigm and utilizes a case study approach (Mills et al., 2010). The context-dependent knowledge that we glean from it takes into consideration the idiosyncrasies of the examined case, including its different elements, such as students, teachers, resources, and overall culture (Case and Light, 2011). As the data did not allow for a fully worked-up grounded theory, the main analytic method used in this work is thematic analysis (Braun and Clarke, 2006).

Research setting

This study examines a unique engineering education program, which involved high school students in the design and assembly of a fully functional CubeSat that was subsequently launched to space. CubeSats are a type of a very small satellite, based on a standardized unit of mass and volume (10 cm × 10 cm × 10 cm). CubeSats have been incorporated into education in several previous initiatives, but to the best of our knowledge, ours is the first study of a satellite building project conducted at a high school. One study, for instance, followed engineering graduate students while developing components such as antennae for inter-satellite communications (Martínez Rodríguez-Osorio and Fueyo Ramírez, 2012). Another studied students from Cal Poly and Stanford, who were involved in developing the CubeSat standard (Lan et al., 2006). These studies, however, are quite superficial, only briefly describing the programs and the authors' impressions of them.

The program examined here is the Duchifat program—a CubeSat-based program, which involves 12–18-year-old students in the task of engineering, integrating, and testing a satellite. The program was a joint endeavor by an extracurricular science center for high school students situated in a major city within Israel's central urban area and a Southern Israeli high school. This study follows the construction of Duchifat 3, the third of a series of satellite-building extracurricular projects undertaken by high school students, focusing specifically on the participating students from this high school.

The Duchifat program was designed as a project-based learning experience. According to a recent review, PBL is the dominant educational paradigm used in interdisciplinary engineering education (Van den Beemt et al., 2020). PBL in engineering education can expose students to core engineering competencies (Nguyen et al., 2020).

Research participants and program description

Participation in the program was voluntary and required students to be in the top 25% in their class in science, mathematics, and English. More than 20 students started this program, but only 15 students from the high school completed it. Thirteen of the who eventually finished the program also agreed to take part in this study. However, not all the participants in the study were able to complete all the research tools. The program had a high attrition rate, and the study demands proved to be too much for some of the participants who elected to drop from the research. The study was thus completed by only seven participants in total (Table 2). All names given in this paper are pseudonyms in order to protect the participants' anonymity. Participants who did not finish all research tools but appear in some of the observed interactions are referred to as "student." Because this study focuses specifically on the development of the participants' systems thinking, we will focus on the case studies of four of the participants that exemplify the trends we observed. A comprehensive and detailed description of all the participants would be well beyond the scope of this paper.

TABLE 2 Details of participants that finished all research tools.

Name	Gender	Grade at start of project	Other electives	Position in project	Remarks
Andy	M	11th	Physics	CEO and head of ADCS	
Michael	M	11th	Physics	Head of EPS	
Adam	M	10th	Physics (switched to mechatronics later)	EPS team member	Research project in Biology involving remote sensing
Diana	F	10th	Physics	ADCS team member	Joined several months into the project
Sarah	F	10th	Art	Communications team member	Joined several months into the project
John	M	10th	Physics	Head of communications	Ham radio enthusiast. Research project in physics that was related to communications
Morton	M	10th	Mechatronics	EPS team member	

The satellite designed in the Duchifat 3 program was a CubeSat—a satellite composed of 10 cm × 10 cm × 10 cm cubes that can be fitted with different components, which can be bought off-the-shelf from various companies. The satellite was designed as three cubes joined together (3 U) to create a 30 cm × 10 cm × 10 cm structure. Subsystems included an Electrical Power System (EPS), communications system, Attitude Determining and Control System (ADCS), On-Board Computer (OBC), and an RGB camera as the main payload.

Figures 1A,C show the satellite at the initial stage of testing upon its arrival at the school. The initial stage of testing, which consisted of turning the different subsystems on and off was conducted by some of the participants. The students worked in teams, participating in various aspects of the satellite's design, as well as a number of design reviews. These reviews consisted of a preparation period of 2–3 weeks, where students prepared presentations of their work and were reviewed by staff and various experts. The preparations for these reviews and other learning activities entailed the analysis of system models and their construction. The modeling activities necessitated cross-level reasoning in order to consider subsystems and their components (which are subsystems themselves) and considering system characteristics, such as boundaries, input and output, components and their interactions. The systems engineer's practices led to the implicit introduction of these strategies.

The students were also involved in the operation of the ground station that was created in the school (Figure 1D).

It is essential to emphasize that this program is an after-school program and that an expert systems engineer led the majority of the learning activities. The nature of the tasks necessitated verbal instructions, and the work was performed in line with the systems engineer's implementation of industry practices and standards. Therefore, we are unable to provide the materials that would have been accessible if this program had been included in the standard curriculum.

Figure 1B shows a diagram of the satellite's subsystems which the participants analyzed and used as a resource in their models of how the different subsystems interact in terms of both hardware and software. The analysis of this diagram entails considering system characteristics—identifying the components, how they connect with each other and their interactions, their input and output when considering them in terms of hardware and in terms of software and data transfer. Going into further details regarding the subsystems of these subsystems entails cross-level reasoning (for instance, how the reactions wheels, magnetometers and magnetotorquers interact and are controlled in order to implement the function of the ADCS). Some of the students took part in designing testing protocols and scenarios but testing the satellite itself was eventually conducted elsewhere and not by the participants. The satellite was eventually launched from India, onboard the PSLV C-48, on December 11, 2019.

The program began with a semester of preparation, in which lecturers from various universities conducted weekly classes to provide the students with an introduction to the topic of satellites (Millan et al., 2019). The students were then divided into teams (according to their preference and field of interest) and assigned to work on various components of the larger project, under the guidance of expert scientists or engineers. At the program's early stages, the project was guided by a physics PhD student who was in the final stage of his degree. After that, the students were supported by a computer science student in the last year of his first degree and mentored by a professional systems engineer with experience in the space industry. Teachers from the school were also involved with the project at different stages. Their roles were to head the establishment of the ground station in the school, teach and mentor the students and coordinate with the outside experts. Each team of students also independently studied relevant topics, such as the conditions in space that might be relevant to their mission, the satellite's optional components, and other subjects as they became relevant. For a detailed description of the program and its contents, see Table 3.

Although the original program planned for the participants to take part in programming the satellite, the participants described in this paper did not take part in that aspect of the project. They did study some programming and the algorithms of the satellite's software in relation to the various subsystems, but did not participate in writing any code.

The participants mainly focused on learning the scientific background, researching the components and subsystems, and presenting the design to various stakeholders in several design reviews. The design reviews entailed producing models of the satellite at different levels of organization, from the single component (e.g., reaction wheels) through the subsystem (e.g., the ADCS) to the satellite as a whole (e.g., input and output of the entire satellite system).

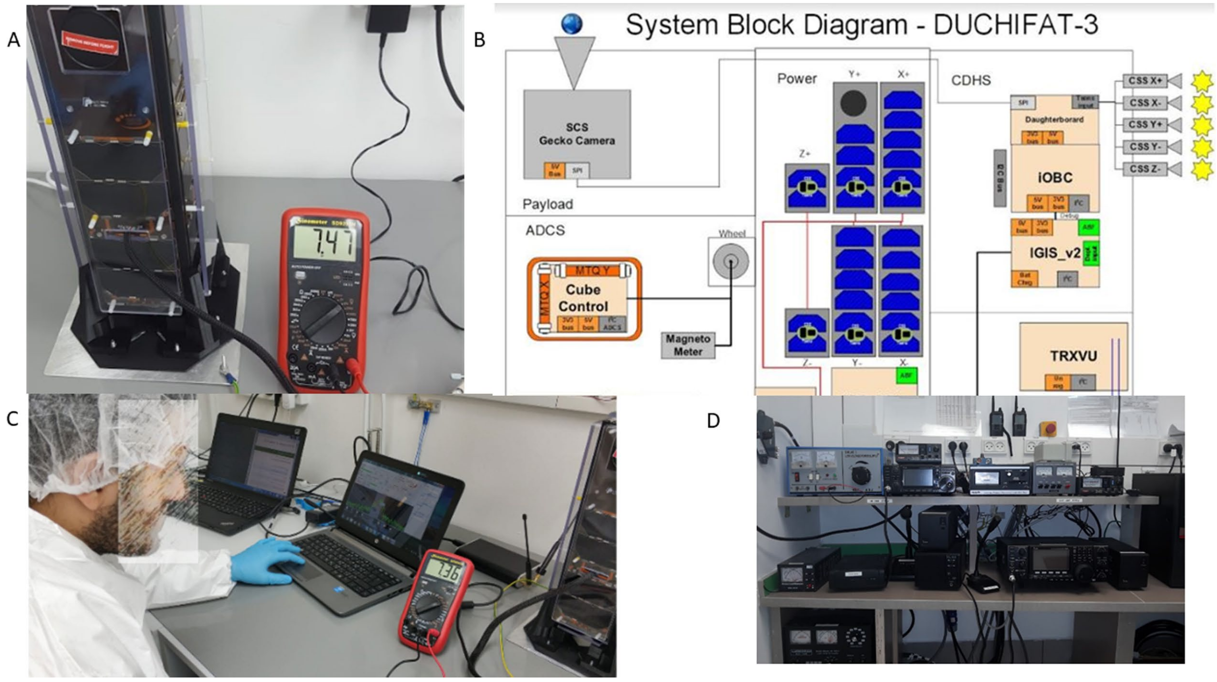

FIGURE 1
The Duchifat 3 CubeSat during initial tests, the ground station and a diagram representing the satellite's subsystems.

They were explicitly asked to consider the boundaries at each scale, the input and output, unintended consequences, system requirements and constraints research tools.

Repertory grid

We used the repertory grid twice—once during months 1–2 of the program and again after month 16 (Table 3). Using the repertory grid allowed us to explore how the participants understand certain terms relevant to their project, subsystems in the satellite, and the various relationships among them. This allowed us to determine the level of sophistication in the participants' understanding of these concepts and their level of systems thinking. Comparing their sophistication level at the beginning and end of the program can illuminate the process that the students went through while participating in the project, (i.e., whether their understanding of the subject matter changed and whether they made any progress in their systems thinking).

The building blocks of the RG are elements (the topics of study within the domain of the investigation), constructs (the participants' ideas about these elements), and ratings (relations among elements and constructs as viewed by the participants). Elements can either be supplied by the researcher, or elicited from the participants themselves (Latta and Swigger, 1992). In this case, they consisted of a list of terms obtained after consulting several academics and industry experts.

Each provided a list of 15–20 terms that they deemed most important for a student participating in such a project to understand. These lists were pooled together, and each term received a numeric score based on the number of times it occurred. The 15 top-scoring terms were gathered into a new list of terms: ADCS, communications, launch, remote sensing, EPS, flight software, rockets, structure design, thermal control, solar panels, payload, orbit control, tests and integration, space environment, telemetry, and command. These elements represented all the subsystems within the satellite (ADCS, EPS, etc.) as well as parts of those subsystems (solar panels). The list also contained processes (structure design, thermal control, etc.), elements that are peripheral to actual satellite-building (launch, rockets), and non-physical elements (flight software).

Constructs represent the participants' interpretations of the elements and the relationships between them. This study employed the most common method of eliciting constructs, the triadic elicitation process, in which the participants are asked to compare three elements and describe in what ways two are similar to one another and different from the third (Hunter and Beck, 2000; Edwards et al., 2009). Each participant drew eight triads for every RG interview.

From these descriptions, we extracted a short sentence to represent the construct that was reflected by the participant's explanation, using the participant's own words as closely as possible. These were then used to create a bipolar description relating to the components of the investigation. For example, a student may say that the ADCS and EPS are both subsystems in the satellite while the space environment is not. From this, the researchers would deduce the construct of a subsystem/not a subsystem in the satellite.

In the second stage, the participant received a large table containing all the elements (terms), one in each column, and the eight constructs, one in each row. They were then asked to rate, on a scale of 1–5, the strength of the relationship between each term and each of their constructs, where 1 represents the strongest relationship and 5 the weakest. For example, regarding the construct of a subsystem/not

TABLE 3 Description of the program.

Month	Engineering content	Scientific content
1–2	Opening sessions - background and expectation coordination.	
3–4	Group work to learn about satellite specifications	Study of space environment and conditions such as temperature, radiation, etc.
5–6	Preparation of preliminary design review (PDR)	Power and supply of different subsystems.
	Defining constraints	Solar energy
	Defining specifications and demands	Mechanics and angular movement (Inertia moment, center of mass, and reaction wheels)
	Devising alternative solutions for the satellite's mission	Electromagnetic signals, radio waves and radio communications, communications balance, receiver and transceiver, antennae, and frequencies
	Devising alternative solutions to different problems and mission needs, and the system's architecture	Thermal aspects, thermodynamics, and structural integrity
	Devising solutions for the satellite's algorithms	Remote sensing fundamentals
6	Presenting PDR in front of extended staff and various stakeholders	
7–8	Preparation of Critical Design Review (CDR)	Electricity balance
	Choosing the most suitable solutions	
	Determination of the satellite's configuration	
	Determining the final design	
9	Presenting the CDR in front of extended staff and various stakeholders	
10–16	Integration review—Integration of subsystems	Writing test protocols for the different subsystems and their integration
	Preparing test protocols	
	Various tests and QA (Some of the participants conducted preliminary tests upon the satellite's arrival)	Determining EPS algorithm parameters

The timeline spanned two school years, excluding summer vacations.

a subsystem, a student may indicate a high relation (1) for the term "communications," and a low relation (5) for the term "launch."

The three building blocks, (elements, constructs, and ratings) were mapped onto a grid using Rep Plus v1.1 software. This software calculates correlations between the elements as well as between the constructs based on the participant's ratings, and presents grids of relations that demonstrate how similar the participant perceives them to be. The more similar the ratings are for two constructs or two elements, the higher they are correlated by the program. An example of such a grid with its explanation is given in Figure 2.

In the top part of the grid the two polars of each construct are written on opposite sides of the table, which shows the ratings given by the participants. The scale above the constructs on the right side indicates the degree of similarity between the constructs based on the point at which they branch out. The list of elements is written on the bottom and organized by the degree of similarity which is indicated by the point at which elements branch out. Thus, the more similar a participant perceives two elements to be, the closer they would be to each other. For further explanations of the method see Rozenszajn et al. (2021).

Observations

Participatory observations were carried out throughout the program by the first author, and audio recordings of several of those observations were transcribed verbatim by a research assistant. One major activity, where students were preparing for a preliminary design review by producing a presentation that described the proposed software architecture, was videotaped and analyzed.

Analytic process

The data presented here were discussed by the authors throughout the analytic process until we were able to reach a consensus. The first author was deeply involved with the project and took part in most activities—both documented and undocumented. In essence, he performed participant observation—a central method in cultural anthropology, in which the researcher takes part in a group and participates in its daily activities, interactions and events (DeWalt and DeWalt, 2011). Doing this allowed the first author to gain an extensive familiarity with the participants. The other researchers had only a few very brief encounters with the participants. These different positionalities allowed us to gain an in-depth understanding of the participants and their experience, while ensuring the validity of our interpretation of the data.

Repertory grid analysis

Each of the seven participating students produced two repertory grids—one pre and one post—representing the constructs arising from their descriptions of the elements they had picked and the relationships between them. We then compared the grids from the end of the project with the ones

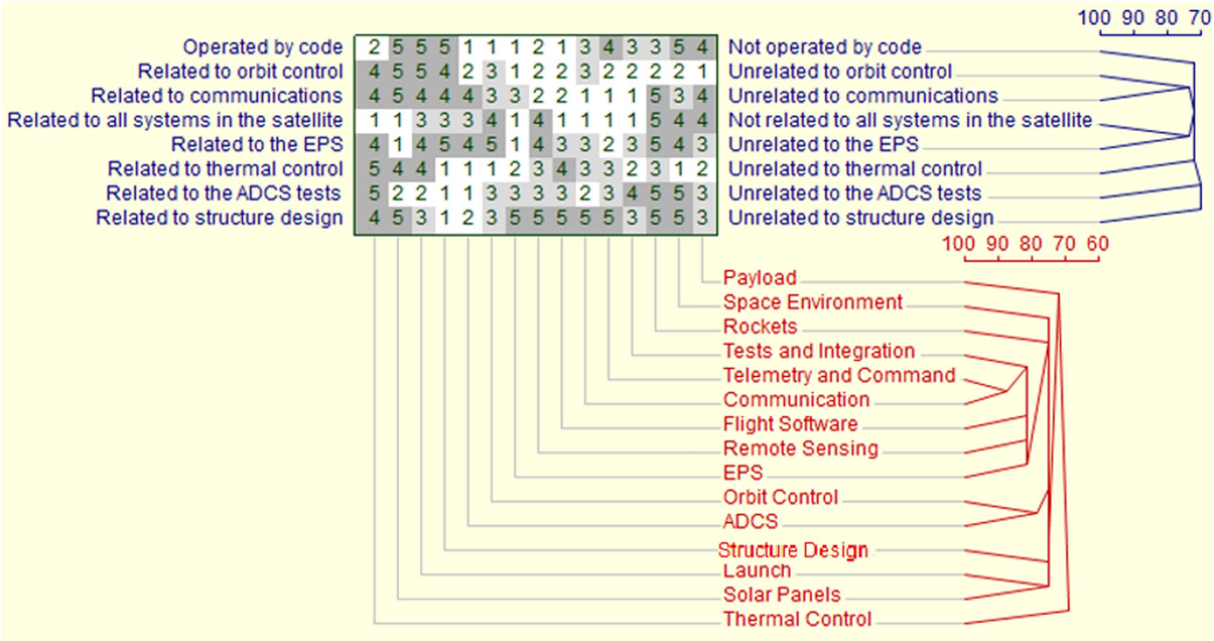

FIGURE 2
An exemplar repertory grid from the beginning of the study.

TABLE 4 Examples of how structures, behaviors and functions are displayed in the repertory grid interview.

SBF model	Elaboration	Exemplar construct
Structures	Referring to the solar panels or one of the satellite's subsystems as components.	Similar elements: solar panels and EPS, distinct element: orbit control.
		"The solar panels and EPS are important parts of the electricity system, while orbit control is not directly related."
Behaviors	Referring to the necessity of electricity provided by the EPS for the other subsystems to work, or to how certain subsystems or components operate.	Similar elements: T&C, EPS. Distinct element: payload.
		"EPS provides electricity to the satellite and T&C tells it what to do with the electricity."
Functions	Stating that the communications system is supposed to transfer telemetry from the satellite to the ground station and commands from the ground station to the satellite.	Similar elements: communications, T&C. Distinct element: structure design.
		"The communications system is in charge of transferring T&C from the satellite to the ground station and commands from the ground station to the satellite"

from the early stages, which allowed us to infer the development of each participant's perceptions regarding these terms. In the second stage of analysis, the elicited constructs were grouped into primary categories according to SBF theory (Hmelo-Silver and Pfeffer, 2004; Goel et al., 2009). We used the SBF model to determine the level of sophistication of the understanding exhibited by the participants (Table 4).

This categorization process was conducted separately and discussed by the researchers until a consensus was reached.

Results

Systems thinking

We analyzed the participants' answers in the first stage of the repertory grid, assigning each construct to either the structure, behavior, or function category. The results are presented in Figure 3.

Overall, participants demonstrated varying degrees of change in their system thinking. As Figure 3 shows, most participants had constructs categorized as functions even at the start of the program. An exception to that is John who had no functions in either occasion, while Sarah moved from having none at the first to having two at the end. Interestingly, we found that the participants' system thinking development was dependent on the roles they assumed in the program and on how broad their involvement was with the project. We illustrate this point below using four representative case studies. However, it is important to stress that the other three participants exhibited the same pattern and were not included for the sake of brevity.

John's case

John was a gifted student who was also a ham radio enthusiast. He skipped a grade in primary school and was involved in an advanced mathematics program in one of the Israeli universities. He served as the head of the communications team and managed the ground station which was built in the school. He was very involved with the

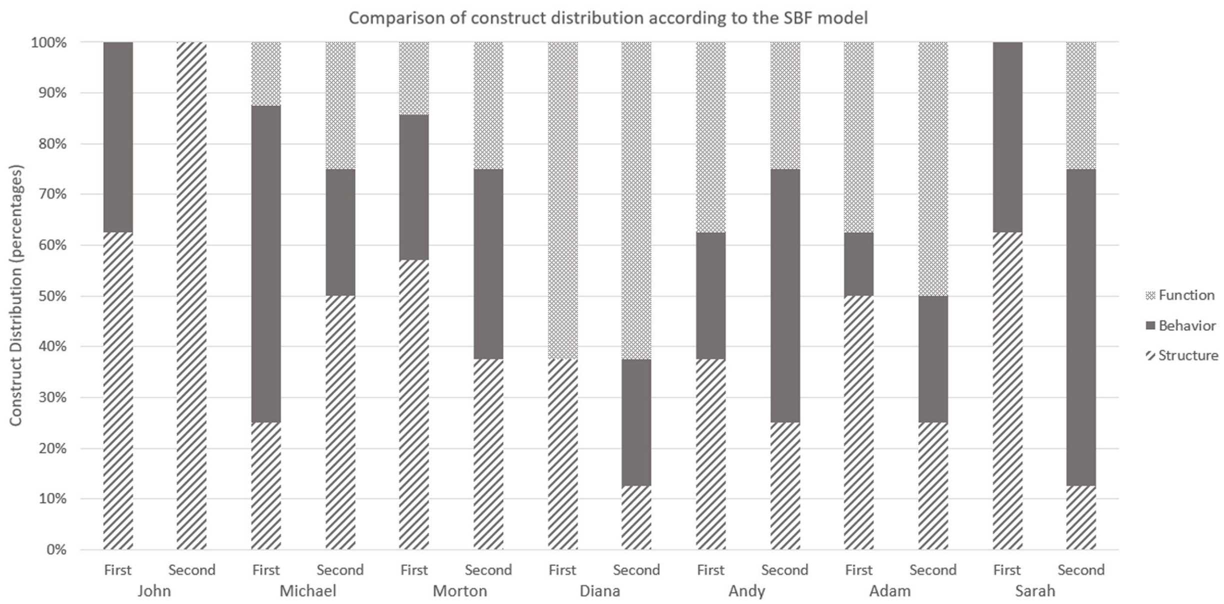

FIGURE 3
Participants' construct distribution.

communications aspect of the project, but refrained from involving himself in any other system and refused to delve into programming, which the students were encouraged to do. He was one of the few students who were able to finish their research projects, which also focused on satellite-ground station communications. Thus, John was deeply involved with a narrow aspect of the project.

In his first repertory grid (Figure 4), John referred primarily to structures, but also to some behaviors. For instance, he said that "T&C is bidirectional [from the earth to the satellite and vice versa], while the launch and ADCS is only leaving the atmosphere." He implicitly considers the boundaries of the earth and satellite systems and their input and output. However, even though he referred to the behavior of the communications system, and implicitly considers system characteristics he did so in a perfunctory way. In the second repertory grid (Figure 5), all of John's constructs were categorized as structures. He said, for instance, that the "EPS is a system in the satellite while structure design and launch are stages in getting the satellite into space." He did not refer, however, to the importance of structure design in withstanding launch (which might have been considered a function). He could also have considered the EPS as a component which plays a major role in the process of structure design but did not do so. In another answer, he said that "the ADCS and the payload are both systems in the satellite, while tests and integration are a stage in the satellite's development." In doing so, he disregarded possible non-structural connections between the elements, like the function of the ADCS in allowing the payload (RGB camera) to perform its function. Moreover, although he referred to the ADCS and payload as systems, he did not exhibit meaningful consideration of system characteristics. All in all, John did not show any progress in his perceptions of the complexity of the system, and maybe even regressed in that regard. He went from mentioning a few behaviors at the beginning of the project to only referring to structures at the end.

When comparing the grid maps, we can see that in the first, the most related elements in his eyes were thermal control to communications, structure design and space environment, and remote sensing and orbit control (Figure 4). However, in his second repertory grid, he considered flight software, payload, and solar panels to be identical in terms of their ratings (Figure 5). His ratings show that he rated all three in the highest degree of relation to all his constructs. However, we would expect that at least in relation to outside/inside the satellite, some discrimination between the three would be evident. Thus, here he exhibits a lack of consideration for the system boundaries.

This lack of nuance seems to suggest a lower degree of complexity in John's understanding of the satellite as a system. The appearance of elements perceived as identical in the second grid also suggests a lack of progress, if not regression, in his systems thinking. Not only did he not explicitly consider system characteristics, it seems that his previous implicit consideration for system boundaries and input and output was lacking in his second repertory grid. This is corroborated by the results from analyzing his constructs through the SBF model.

The high relatedness of communications to structure design is a bit puzzling as well, since there is no reason to relate those two elements closer than any other subsystem. This may indicate the centrality of communications in his eyes, since he dealt with that subsystem almost exclusively. Since structure design involves all the subsystems and their components this can also be attributed to his lack of cross-level reasoning, where he did not understand the relationships between different levels of organization.

As mentioned before, John was quite involved with the project and was a gifted student who achieved advanced learning goals. We therefore feel safe in determining that the reasons for his lack of progress with regard to systems thinking are a result of neither cognitive difficulties nor lack of engagement. His narrow focus on the communications aspect was evident not only in his choices (i.e., focusing only on communications and avoiding any other aspect like programming, and his choice of research project), but also in our observations of him during the learning process. In an activity where

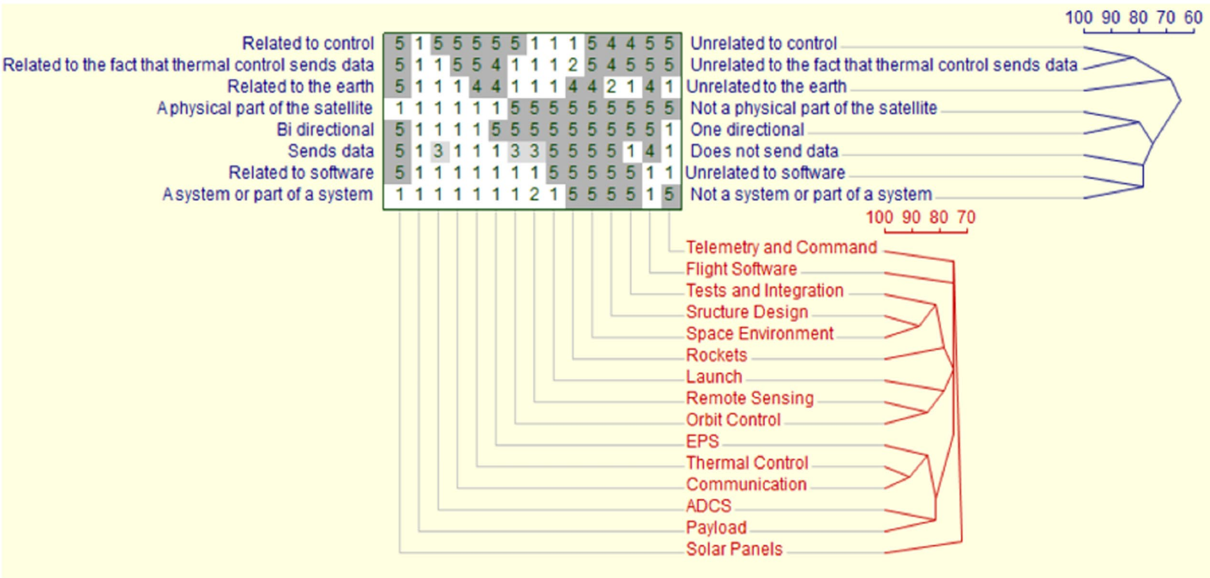

FIGURE 4
John's first repertory grid.

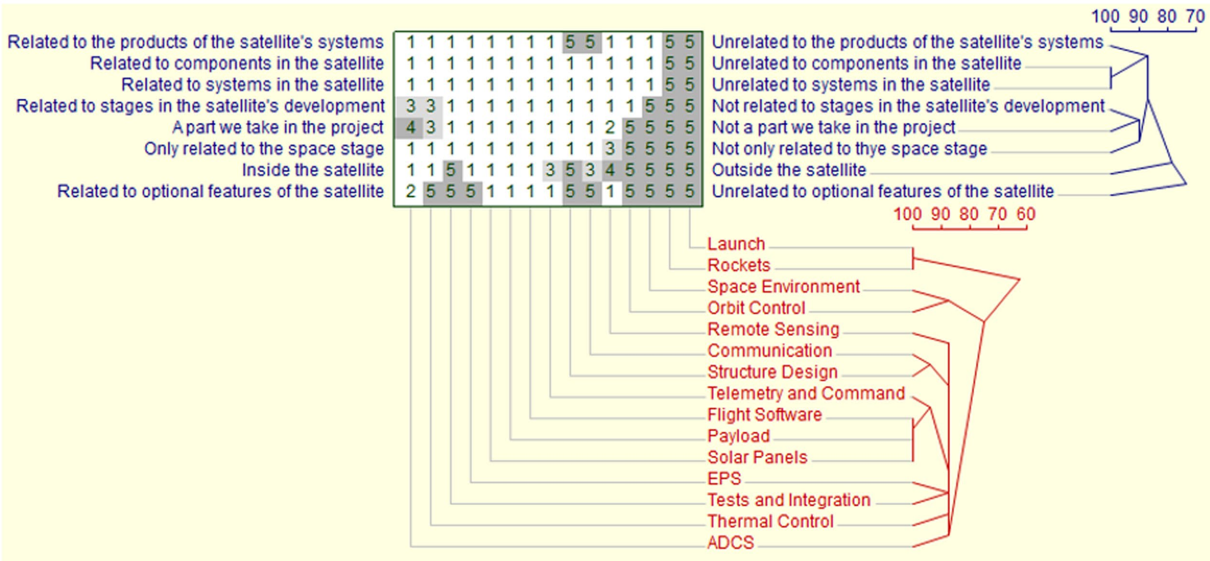

FIGURE 5
John's second repertory grid.

the students were producing several models of the software architecture, software demands, and the relationships between subsystems at various levels, he was expressive only when the communications system was very explicitly brought up. He was quiet throughout discussion of the ADCS system, in which students from various teams participated, but as soon as the communications came up, he became very vocal:

> Teacher: What goes into the TxRx?
> John: Commands are going in.
> Teacher: Commands?
> John: Like, input… all sorts of input go in, noise.
> Teacher: What goes out?
> John: A receiving signal, roger, acknowledged.

This exchange went on exclusively between John and the teacher, where John displayed a comprehensive familiarity of the communications system. However, when the communications system's relations to other systems came up, John became less sure of himself, and other students became part of the discussion:

> Teacher: What else goes into this system? Not necessarily from the outside, but from the inside as well?
> John: Electricity.
> Teacher: No, that's not a system capacity.
> Andy: Its capacity is to relay commands.

Here we see an example where Andy, who is the head of the ADCS team, gets involved in the discussion regarding the communications system. This behavior was displayed by Andy throughout our observations of him, but was not displayed by John. John's reluctance to involve himself with any other aspect of the project other than communications was very noticeable throughout our observations. Since he did not take an active part in considering how the communications subsystem relates to other subsystems, thereby also not thinking about the satellite at higher levels of organization, it may not be surprising that his systems thinking did not show progress. Andy, who we describe next, showed quite the opposite tendencies.

Andy's case

Andy was a very active student in the project. He started as the head of the ADCS team. During the program, the students assumed the roles of a quasi-independent organization and Andy was chosen to serve as CEO. He involved himself with all aspects of the project, communicated with all teams and was active in representing the project and school to visitors. He chose not to complete his research project, which was supposed to be related to the testing and integration of the satellite.

Andy had representations of all the categories in both repertory grids. For instance, when he explained the connection he saw between the EPS and the solar panels in the first repertory grid (Figure 6), he said: "both terms are related to the EPS. One is the EPS itself and the solar panels are part of the EPS." He noted the hierarchy between the two elements, and identified the different levels of organization but not their relationship in terms of their functions or behaviors. In another triad, he said that: "T&C is an ability the communications system can perform."

He thus referred to the behavior of the communications system, if only in a perfunctory way. He was also able to consider functions: "The solar panels generate electricity with which you can send T&C to the different systems." He considered the function of the solar panels and connected the generation of electricity to handling T&C.

In his second repertory grid (Figure 7) Andy described more functions, but perhaps more importantly, his reasoning seemed more complex. For instance, he said: "The EPS operates different systems in the satellite. It activates wheels and other things. As a byproduct, it causes the satellite to heat up and the thermal control moderates that phenomenon." Andy's description here goes beyond merely noting two elements that affect one another. He considered unwanted consequences of certain elements through a series of connections. He was also aware that solutions are not complete, since he used the word "moderates," and not "solves," for example. He also identified causal relationships between different levels of organization of subsystems, subsystems' components and their relation to physical processes such as the buildup of heat. Andy's recognition of cause and effect as a series of couplings (EPS–reaction wheels–thermal control), and his concern with the regulation of excess heat, which suggest he is taking the dynamics of the system into consideration are indicative of progress in his systems thinking. We can also see various related elements in his grid, but no identical elements, as opposed to John. This demonstrated a high resolution in his thinking. For instance, remote sensing and payload could have been considered identical by participants, since their payload was a camera, yet Andy makes a distinction between the two.

In an activity where the students had to represent their systems in different levels of organization, Andy tried to figure out how the remote sensing system was represented (even though he was in the ADCS team). He spoke to another student about the remote sensing system:

> Student: What's this whole thing on the board?
> Andy: That's the system. Actually, that's level 2, which begins at the…first level. Actually, that's the whole satellite. So, what's level 0?…
> Andy: So, what are we doing? Imaging?
> Student: Yes, that's in the camera.
> Andy: And where does it go? Here?
> Student: Yes, and then it goes out, image data.
> Andy: What goes out?
> Student: The image data, the index, I do not know.
> Andy: What do you mean you do not know? You took an image, what data do you have?
> … I'm asking because I do not know. I want to know… So, I'm guessing what the image data is, maybe it's its size, date, time…

As in the previous instance, where Andy involved himself in the communications system discussion, here he involves himself in the remote sensing system. He is asking questions, thinking across levels when considering different levels ("that's the whole satellite, what's level 0?"), trying to identify connections and making educated guesses. His tendency to initiate discussions with other teams, thinking about other systems and not only his own, may have contributed to the development of his systems thinking.

Sarah's case

Sarah was a gifted student who joined the program (on the communications team) 2 months after it began. She wrote a research proposal that was accepted in computer science which would have been equivalent to a full matriculation exam. Her research proposal dealt with trying to develop an algorithm that could use the input from the camera to determine the satellite's attitude and position. She made progress on her project but chose not to finish it. However, she did a lot of research into the ADCS and remote sensing parts of the project, as well as programming in MATLAB. Sarah was involved with various aspects, but put less time into the program than other participants. Still, she was able to display a marked progression in her systems thinking. Our recording of a communications assignment in which she participated showed her to be very active, demonstrating understanding and engagement. The communications team were modeling their system by creating a 2D representation:

> Sarah: Let us move that up and connect this. Now let us move to the manager. Let us see, it connects to these two, does not it?
> Student: Yes.
> John: The manager goes to…
> Sarah: Both through here and here.

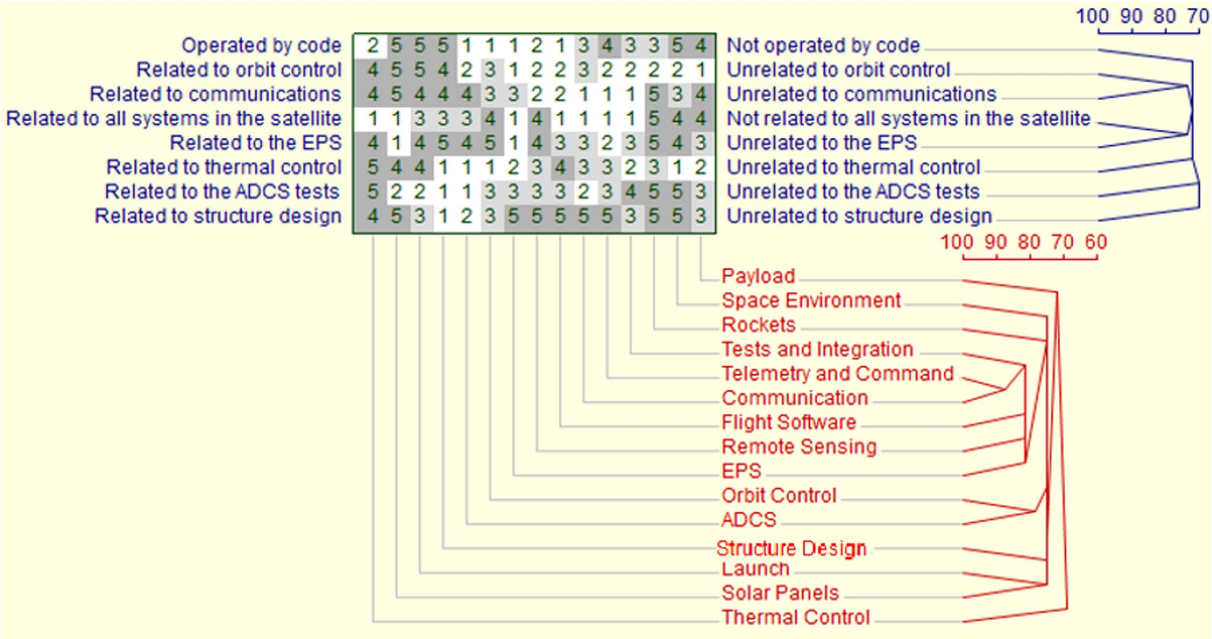

FIGURE 6
Andy's first repertory grid.

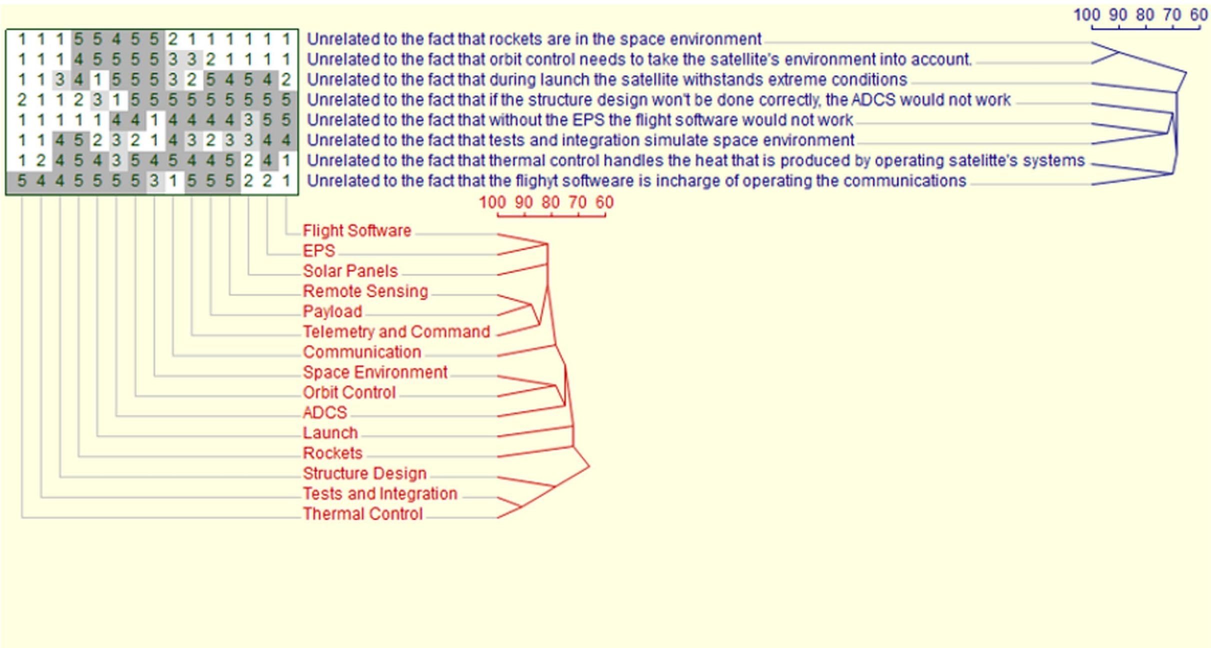

FIGURE 7
Andy's post repertory grid. The left side constructs are truncated for the sake of readability.

Despite joining the project late, Sarah was quite involved with her team, as we can see from her making suggestions and observations regarding their model. On other occasions, we observed her helping other teams. She also wrote a reasearch proposal for a five-point CS credit, where she was planning on designing a star sensor as part of an ADCS system. She started working on her personal project for quite some time, but was unable to finish it. Thus, she did not limit herself to the sub-system team she initially joined, but was broadly involved with other aspects of the project.

When analyzing her constructs through the SBF framework, we can see that she showed marked advancement in her systems thinking, from focusing on structures to focusing on behaviors and

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functions. For instance, in her first repertory grid, when explaining why space environment is less related to ADCS and communications, she states: "space environment refers to the position [of the satellite]" (Figure 8). In her post repertory grid (Figure 9), on the other hand, she addressed the control flows, feedback loops and dynamics of the satellite. For instance: "There are times when there is no communication with the satellite and the flight software compensates for that." Thus, she is considering system characteristics in her reasoning.

Her pre vs. post repertory grids show a shift from considering simple relations, such as "related to the satellite's orbit," to more complex interactions in the form of her construct: "related to the fact that space environment determines the orbit." She also referred to various control processes in her post grid, which were lacking in the pre grid. This shows development of her systems thinking, even though she spent less time on the project. As a byproduct of her lower consistency in attending the group sessions, she was involved with various teams and aspects of the project, and that may have contributed to her systems thinking.

When describing her research proposal in her reflective interview, she said:

> At the beginning I wanted something else, to examine something else related to images of stars. That would have required much bigger images, not like the ones from our satellite. I was trying to come up with something else and then I read a few interesting papers about the use of star sensors. I got very excited and if we can determine not only the attitude of the satellite but also its position. I saw this method that also uses Earth sensor. I thought I might be able to combine them and use a star sensor instead of the Earth sensor. We'll see if it works.

This too reflects how she further broadened her interests beyond what her team, communications, focused on. Even though she was not able to complete her project, her research in the context of writing a proposal exposed her to various aspects of ADCS features and remote sensing.

Adam's case

Adam was part of the EPS team. At the project's outset, Adam displayed a lack of confidence in his ability to contribute. He had some misgivings regarding his ability to participate, and especially to carry out a research project.

> Q: If we are talking about questions, do you expect any difficulties [in the project]?
> Adam: Sure, it is not easy, this satellite thing.
> Q: Why is not it easy?
> Adam: Cause it is a lot of stuff.
> Q: What do you mean a lot of stuff? Like what?
> Adam: All the studying, we are just joining this, it is not as if we have knowledge to begin with.
> Q: How is that any different from any other subject?
> Adam: You need to do research here. It is not as if you have material you need to study. You need to research by yourself.
> Q: What do you mean by research?
> Adam: This whole satellite programming, the EPS, we need to study it, we do not know what it is. It is not like a teacher already knows it and just explains the code to us. We're studying it together from the beginning.
> Q: Do you think that will be hard for you?
> Adam: Yes.

Adam took part in the various activities and group tasks we observed. He was never the most prominent member in the team, and other members demonstrated more involvement and leadership in the teamwork. However, the subject he chose to study in his personal research project was quite different. He studied dynamics of algae in a freshwater lake (the sea of galilee) using remote sensing. His research project was equivalent to a five-point matriculation exam in biology and received a very high mark (97%). Thus, he studied remote sensing in addition to his part in the EPS team. Moreover, he had the opportunity to deeply explore another complex system in the context

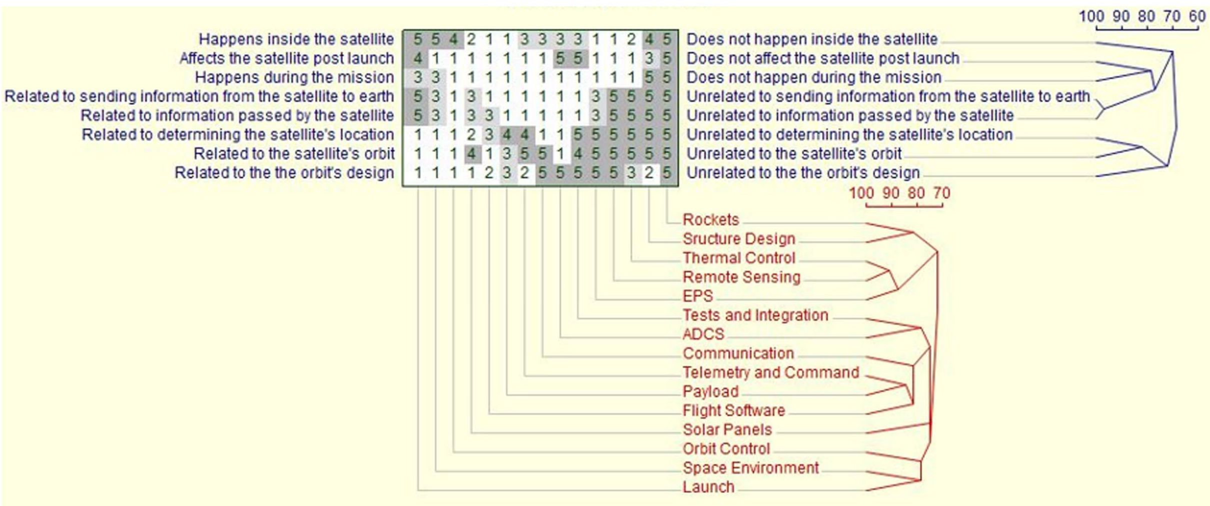

FIGURE 8
Sarah's pre repertory grid.

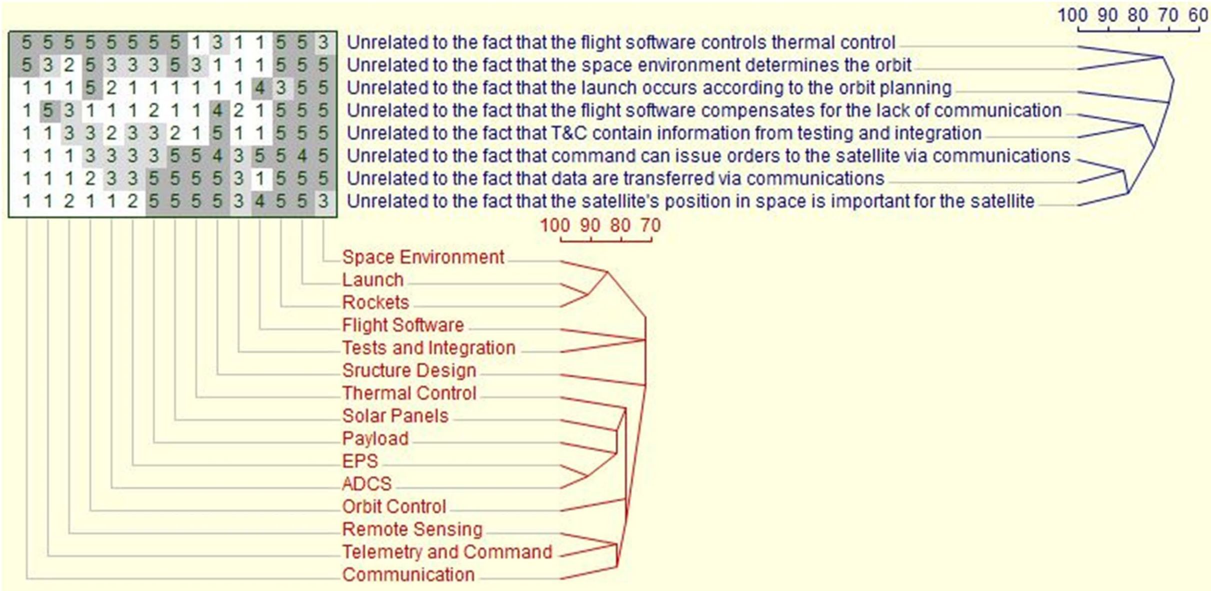

FIGURE 9
Sarah's post repertory grid. The left side constructs are truncated for the sake of readability.

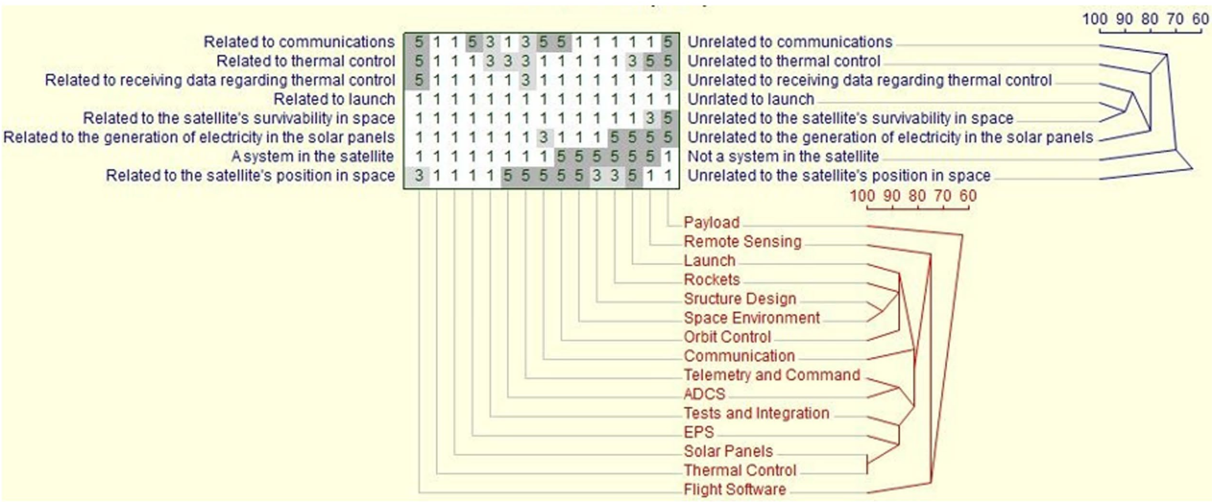

FIGURE 10
Adam's pre repertory grid.

of ecology. In the reflective interview at the study's later stages, his attitude toward his ability to carry out a research project was completely changed, and he was very confident in that regard.

Adam's pre repertory grid (Figure 10) reveals several misconceptions. For instance, he regards solar panels as very closely related to thermal control, perhaps because of his perceptions of their relations to the sun. When considering the triad of "space environment," "solar panels" and "communications," he considered the first couple to be more related, saying "there is no connection between the sun and communications." This argument corroborates the importance he assigns to the sun's influence. In his post repertory grid (Figure 11) this association does not exist.

Another interesting point is that the payload is quite far removed from other satellite systems in his first repertory grid. In the post repertory grid, on the other hand, he recognizes the payload as being more closely related to the other systems. The second repertory grid shows that Adam perceives the various subsystems as closely related, while still making high resolution distinctions between them. It also shows how the complexity of his constructs has increased. He considers the function of the thermal control and unwanted consequences of its hypothetical lack of function ("Related to the fact that without thermal control the satellite will be ruined"). He generally pays more attention to the functions of the different subsystems, instead of mainly referring to them as components (structures) only.

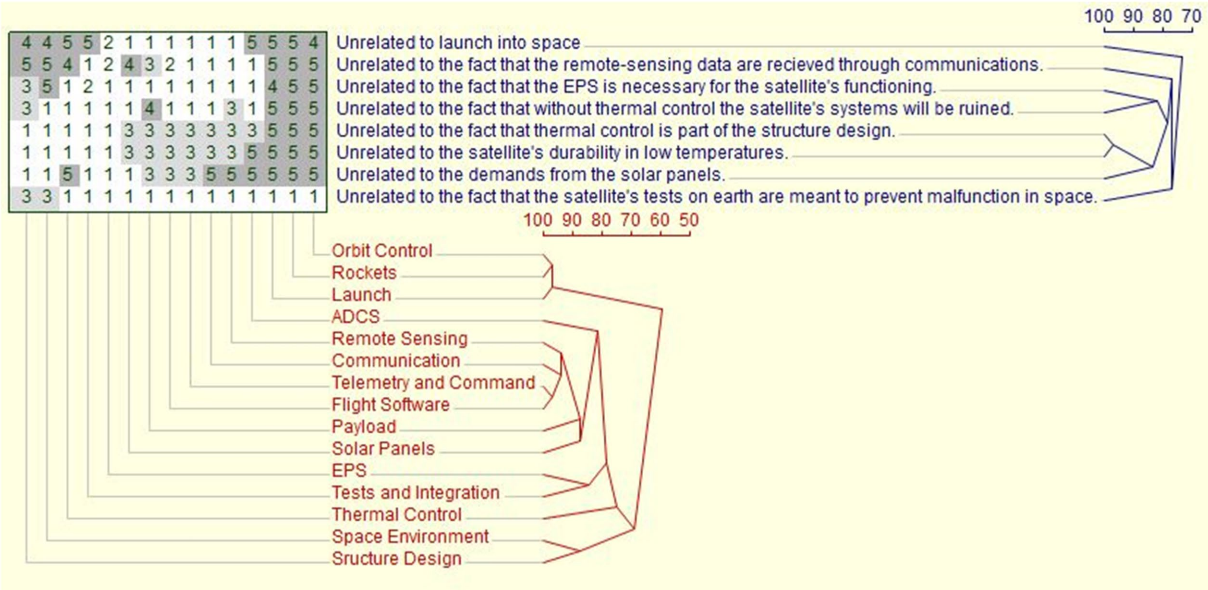

FIGURE 11
Adam's post repertory grid. The left side constructs are truncated for the sake of readability.

Discussion

Understanding complex systems is known to be difficult for students at various stages of their education (Hmelo-Silver and Azevedo, 2006; Schneeweiß and Gropengießer, 2019) and our findings support this. At the early stages of the program, the participants' personal constructs demonstrated a low level of sophistication in their systems thinking. Although they seemed to understand the terms they were given in the repertory grid interview, their constructs revealed a relatively simple understanding of the satellite as a system. In contrast, by the program's end, most participants showed varying degrees of progress in their systems thinking, and for some participants, a much deeper understanding of the satellite as a system. All the participants were very capable in terms of cognitive abilities. Thus, despite the fact that systems thinking is a higher-order thinking skill, cognitive capacity cannot explain the observed disparities in systems-thinking development. The varying levels of systems-thinking growth could not be explained by the amount of time spent working on the project either. These two themes are best shown by John, who was both cognitively adept and devoted a great deal of time to his work on the communications team, but displayed very little systems-thinking growth.

What seemed to explain the differences was the breadth of the different participants' involvement, rather than other possibilities, like level of engagement. By breadth of involvement, we mean the degree to which a certain participant was involved with the various aspects of the project. In other words, the contributing factor was not whether a participant was deeply involved with the program, but rather how many different aspects he or she was involved with.

Involvement with several subsystems allowed students to better identify and understand interrelations between the subsystems, feedback loops (for instance, how the ADCS relies on the EPS to maintain the satellite's attitude and in turn affects the power generation of the solar panels), and dynamic interdependencies. Furthermore, they were able to better identify the intended purpose of their subsystem in relation to other subsystems, which may have contributed to their identification of behaviors and functions in the system rather than only structures. All of these abilities characterize proficient system thinkers (Table 1).

The program designers' reason for focusing the students on narrow roles was to enable them to successfully accomplish the goals of the program without formal engineering education (Millan et al., 2019). However, our study suggests that, with respect to the development of systems thinking, this may be counterproductive. Some might argue that in order to foster the development of systems thinking, education programs need to expose students to a wide variety of ideas and practices in different disciplines (Brookes, 2017). Indeed, systems thinking has been suggested to be closely linked to multidisciplinarity, problem-based learning, design and the management of risk and uncertainty (Milke, 2017).

People with a great depth of knowledge in a single area are referred to as "I-shaped," which can describe most engineering graduates. People with some knowledge in many areas are "dash shaped." The combination of the two is called "T shaped," meaning someone with deep knowledge of one field with broad familiarity with other fields. There are quite a few studies that discuss the benefits of T-shaped education in fostering systems thinking approaches, but most of them advocate for initial specialization followed by acquiring broad skills, also known as soft skills (van den Beemt et al., 2020). This is the common route of first gaining deep expertise in a single area during one's studies while gaining a broad knowledge in many areas during one's career as an engineer (Boehm and Mobasser, 2015; Brookes, 2017).

However, there is a recent approach that suggests that not only should engineering graduates be T-shaped, but also that engineering programs can start by giving the students a broad education before going deep into one area (Boehm and Mobasser, 2015). Our results suggest that even at the high school stage, students may benefit from a broad engineering education, and that the approach of forming teams of "experts" in programs like the one studied here may need to be reconsidered. Still, there remains a question of what may be the underlying mechanisms that can explain the pattern we observed. In other words, why did students who were more broadly involved with various aspects of the project developed a more sophisticated systems-thinking in the context of the satellite? We suggest that broader involvement may have provided more opportunity to engage in practices that foster systems-thinking development.

Under the guidance of the systems engineer, the participants in this study were very involved with models of the satellite, which consisted of 2-D representations of the various levels of organization—from the whole satellite, through its subsystems, down to the individual components of that subsystem, as well as the physical characteristics of the space environment (radiation, temperature) and micro scale processes such as power generation through the solar panels. The practice of modeling was a major part of the participants' work in preparation for the design reviews, as can be seen in our results.

Central artifacts of model-based engineering education are conceptual models of complex systems, which build a common language between the scientific education and engineering education communities by modeling natural or artificial systems (Lavi and Dori, 2019). Modeling is part of scientific reasoning and enables comprehension of complicated systems by employing simpler hypothetical systems that, in certain respects, resemble the complex system they represent. Knowledge about the model is converted to knowledge about the phenomenon (Krell et al., 2019).

Modeling can help students better understand the dynamics of a system and integrate knowledge about it (Wilson et al., 2020). Modeling while studying complex systems allows students to evaluate the system's properties and to express its complexity by depicting the relationships between its components while iteratively revising them. The model revision process allows students to think about the system in new ways (Bielik et al., 2022). The use of models in education consists of two central parts: models that communicate scientific or engineering content *to* students, and modeling done *by* students to gain insight (Upmeier zu Belzen et al., 2019). The latter mode of modeling, which was evident in our observations, is instrumental in making students' understanding visible, helping students organize their ideas, and facilitating constructive and collaborative discussion (Hmelo-silver et al., 2017; Bielik et al., 2021). It allows students to engage in inquiry practices by gathering data, generating hypotheses, and testing them (Hmelo-Silver et al., 2015).

However, the modeling the participants were engaging in consisted of constructing 2D-representations of the satellites systems and components. The fact that they were ultimately unable to test their models may have well been a factor in hindering the development of more sophisticated systems thinking. Studies show that modeling has multiple cognitive benefits in terms of scientific reasoning and understanding (Louca and Zacharia, 2012). However, an important part of modeling is testing the model, revising it and validating it (Bielik et al., 2021; Nielsen and Nielsen, 2021), activities which were lacking in this case. This illustrates the importance of professional development for educators of metamodeling knowledge as Bielik et al. (2021) point out.

Gilissen et al. (2019) have described several system characteristics that are relevant to complex systems in nature. These characteristics include components, interactions, boundaries, input and output, hierarchy, emergence, feedback loops, and dynamics. Although many of the complex systems characteristics may be addressed by generating 2D representations, some may not be. For instance, the dynamics of a complex system in terms of changes in time and space may not be addressed by static representations (Hmelo-Silver et al., 2015). Feedback loops, which also contain a time dimension, can be only partially represented in static models. Modeling in this program was also done mostly with a reductionistic approach where each system was modeled by dividing it to subsystems, while less attention was given to how subsystems interactions may give rise to emergent properties. Thus, it may be worthwhile to employ software that will enable students to create dynamic models that will allow them to explore the system's changes over time, emergent properties, and other system characteristics in a more meaningful way.

Depending on their goals, models represent a subset of the parts of the modeled item. They must reflect certain facets of the examined phenomena and be utilized to produce predictions. Models are evaluated by comparing their predictions with data from the real world and changing them as necessary (Krell et al., 2019). In this program, the students did study the parts that were needed to be modeled and were used to predict the functioning of the satellite. The testing period could have served as a means of comparing the model to the real world and revision of the model, but unfortunately, most of the testing was not carried out by the participants, hence we cannot remark on the meaningfulness of that phase in terms of systems thinking development.

While the participants were involved in modeling, they also engaged in thinking across levels of organization, which fosters systems thinking (Ben-Zvi Assaraf and Knippels, 2022). Weintrop et al. (2016) identify cross-level reasoning as core to systems thinking (though they call this "thinking in levels"). Systems can be understood by analyzing different levels of organization from the micro scale to the macro scale. Different insights can be gained from examining different levels, which can lead to a better understanding of the emergent characteristics of the system as a whole (Weintrop et al., 2016). Challenging students to reason between various levels of organization has been shown to improve systems thinking (Verhoeff et al., 2018; Gilissen et al., 2021). Thus, it may be the case that participants who modeled more subsystems, thereby also utilizing thinking across levels more than participants with a narrow focus, were able to make more progress in their systems thinking. This is in accordance with Bielik et al. (2021), who suggest that repeated use of models in different contexts fosters systems thinking.

Another relevant suggestion is to constantly revisit the level of the whole system. While working on specifics, students may get bogged down in detail and lose the bigger picture, as some of the students in this case might have done by focusing only on the subsystem they were initially assigned to. Deliberately encouraging students to reconsider the satellite as a whole may be an important guideline for complex engineering projects such as the one presented here. Bielik et al. (2022) stress the need to revisit the overarching phenomenon, since students can easily lose the big picture of what they are modeling, and our findings seem to support that recommendation.

A final aspect of the program was the use of explicit systems language by the systems engineer, as we saw in our observations.

Under his guidance, the students were asked to consider the system components and the interactions between them, input and output, system boundaries at various levels of organization, unintended consequences, and the dynamics of the systems. Systems language is the explicit use of terms that refer to system characteristics. Proponents of this strategy contend that when teaching about complex systems and encouraging system thinking, teachers should make explicit use of systems language and encourage their students to use that language explicitly (Eberbach et al., 2021). Deconstructing a phenomenon to its characteristics and discussing them explicitly has been shown to help clarify it for both students and teachers (Klein and Zion, 2015). Jordan et al. (2013) showed that exposure to systems language helps students in their explanations by linking multiple ideas and improving their explanations' sophistication by enriching references to invisible elements. The use of systems language seemed to have been a natural tendency as a result of the instructor's experience as a systems engineer. An engineering teacher who lacks such experience may need to consciously incorporate the use of systems language, since such use supports the development of systems thinking (Fick et al., 2022).

Nguyen and Santagata (2021) have shown that the teacher's prompts greatly affect how middle school students respond when asked about connections in systems. The language teacher's use is adopted by students, not only in their discussions with the teacher but also in their group discussions without the immediate presence of the teacher, thus assisting their understanding of systems (Hmelo-silver et al., 2015). However, since instructors with no experience in systems engineering may not utilize systems language as naturally as the engineer in our program did, program designers need to consider how to deliberately incorporate this language into instruction.

Reflecting on the body of work we have included in Table 1, there are several themes that are involved in systems thinking. We have observed the implicit use of some of the themes by the systems engineer such as the analysis of systems' elements and relationships, consideration of feedback loops and cross level reasoning to a certain degree. Some attention was also paid to the dynamics of the system, but since there was no dynamic modeling, or testing done by the participants, it was limited. Moreover, other themes such as emergence was not evident in our observations. A dynamic model of the satellite, which could be built from physical components that are not intended for use in space, could be very affordable considering the overall budget of such a program. Such a model which could be tested by students, experimented upon and manipulated, could serve as a very meaningful scaffolding for fostering systems thinking. Emergence (Table 1) could be made evident in terms of understanding how the behavior of a system arises from the interaction of its agents over time (Sweeney and Sterman, 2000). Generalizations (Table 1) could be achieved by comparing the model satellite to the satellite itself which could facilitate observing the system from a generic viewpoint—looking for similarity between the system and other systems (Gero and Danino, 2016). Dynamic relationships (Table 1) could be made more explicit by using the model to identify different types of procedural sequences—linear, divergent, convergent, and looping (Lavi and Dori, 2019).

This study has some limitations. The number of participants who were able to finish all research tools is quite small. The program studied here is a very demanding program for students. There is a natural attrition as a result from the participation in the program itself. The research tools used add to that attrition and result in a low completion rate. Since this is a unique program, this study may present a challenge to replicate. We certainly acknowledge that the pattern observed here requires more evidence, but we think it is interesting and important enough to be relevant to most engineering educational programs and any other program that involves the approach of assigning students to narrow roles.

In sum, we suggest that the instinctive use of various strategies by the systems engineer had the potential to facilitate the development of the students' systems thinking. However, for that to take place, students need to be involved with various aspects of the system, in order to engage with the system from different aspects and through different lenses. This broad view may be achieved through students assuming broader roles in engineering projects, or by engaging in different learning activities that research projects can provide. Moreover, since not all learning programs can involve expert system engineers, it may be advisable to design similar programs while explicitly considering the role of modeling, cross level reasoning and systems language in fostering systems thinking.

Data availability statement

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

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

RT collected data, performed most of the interviews, carried out observations, analyzed the data, and was a major contributor in writing the manuscript. OB-Z conducted interviews, reviewed the data, and its analysis and substantially revised the manuscript. SM interviewed experts, reviewed data and analysis, and revised the manuscript. All authors contributed to the article and approved the submitted version.

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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.

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EDITED BY
Laura Zangori,
University of Missouri, United States

REVIEWED BY
Li Ke,
University of Nevada,
Reno, United States
Joshua Rosenberg,
The University of Tennessee,
Knoxville, United States

*CORRESPONDENCE
Elon Langbeheim
✉ elonlang@bgu.ac.il

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

Elon Langbeheim[1]*, Shani Ben-Hamo[1], Gershon Weintraub[1] and Stav Shapira[2]

[1]School of Education, Ben-Gurion University of the Negev, Beer Sheva, Israel, [2]School of Public Health, Ben-Gurion University of the Negev, Beer Sheva, Israel

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

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.

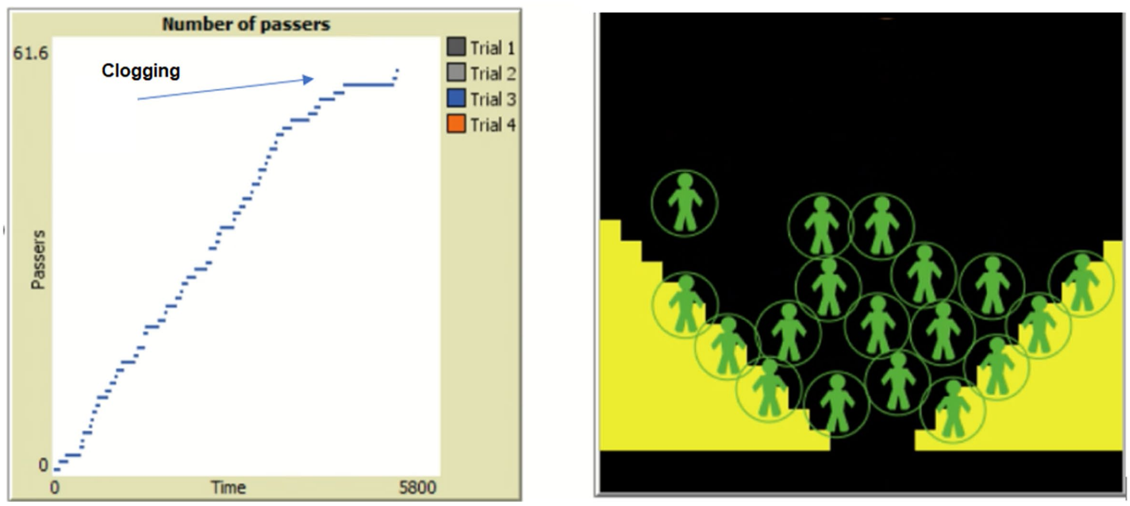

FIGURE 1
A bottleneck simulation in which a crowd moves towards a narrow passage at the bottom of the screen (right). The blue graph (left) shows the number of people that pass through the opening vs. time. The horizontal section marked by the arrow, represents temporary clogging.

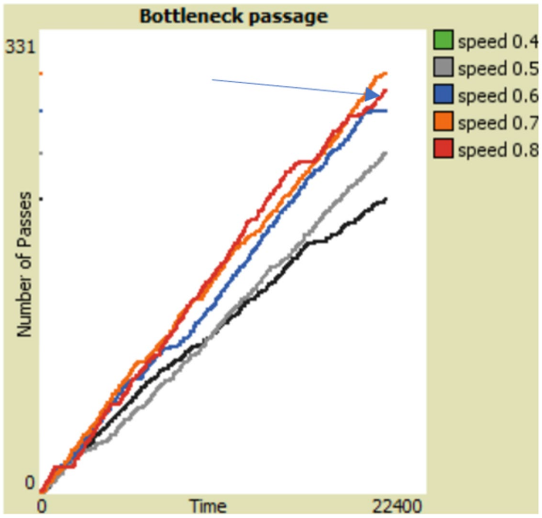

FIGURE 2
A graph showing the faster-is-slower effect to the number of passes increase with speed from 0.4 to 0.7, but then it decreases for 0.8. The arrow shows that the number of passes is lower for the red curve, than for the orange curve.

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.

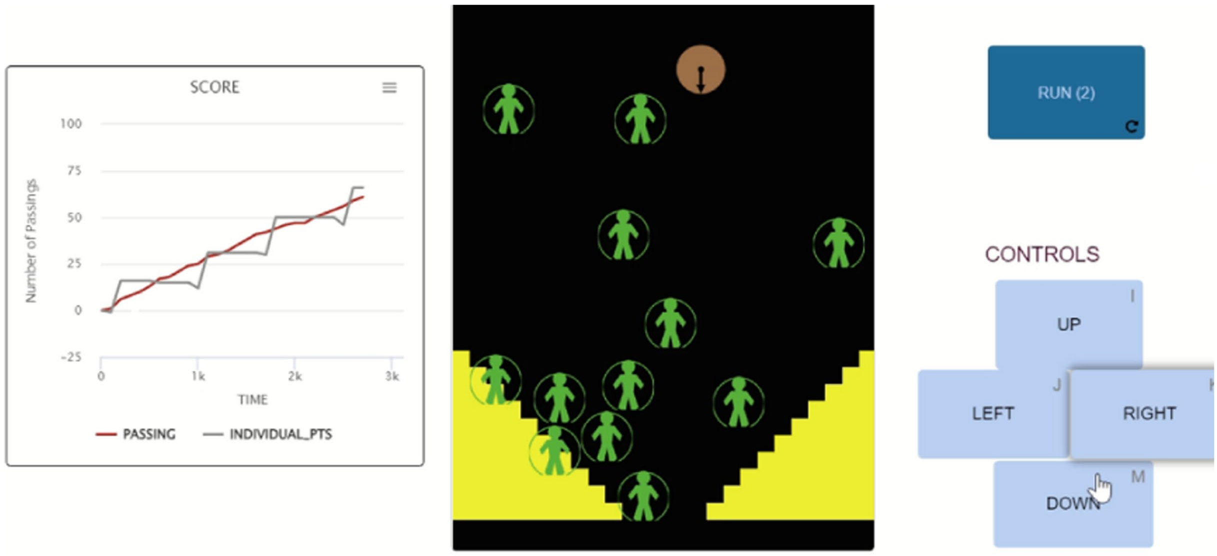

FIGURE 3
the participatory simulation of evacuation through a bottleneck: The brown circle is controlled by the user with the up-down-left–right control keys (right). The graph (left) shows the points gained by the user (20 point for each successful pass, minus one point taken away by each collision)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

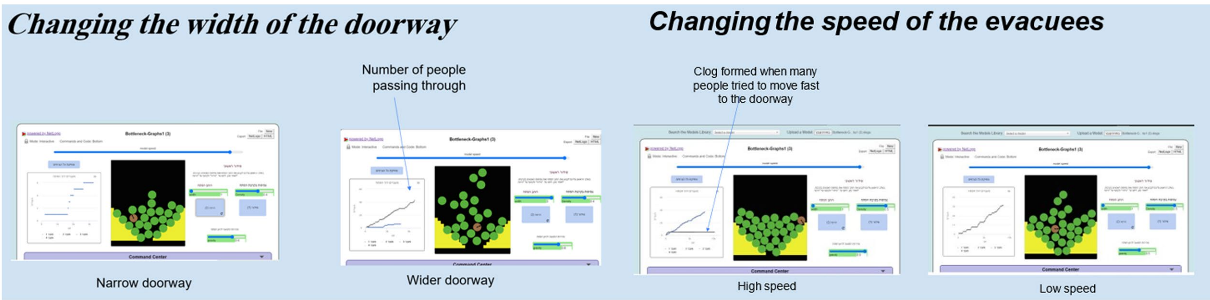

FIGURE 4
Two slides from the presentation shown to both groups, that shows the bottleneck simulation: the width of the doorway (left) and the influence of speed (right) on the passing rate.

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

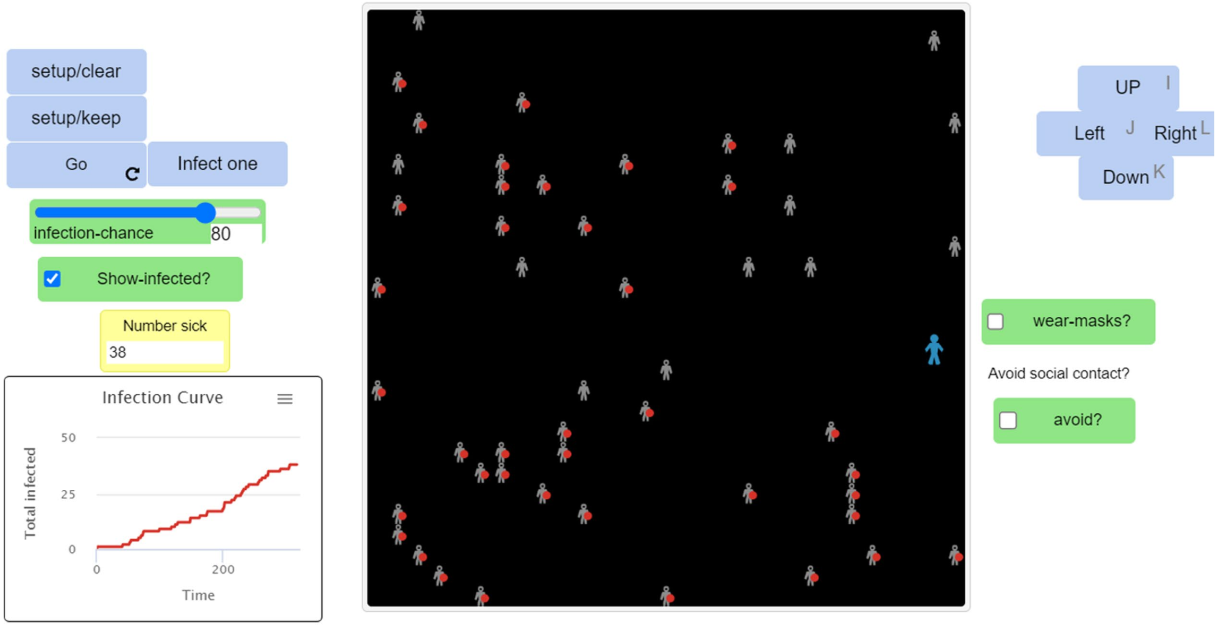

FIGURE 5
The adapted "Disease solo" participatory simulation. The user controls the blue agent. Agents with red dots are "infected" and those without are "healthy." The graph shows the number of infected agents vs. time.

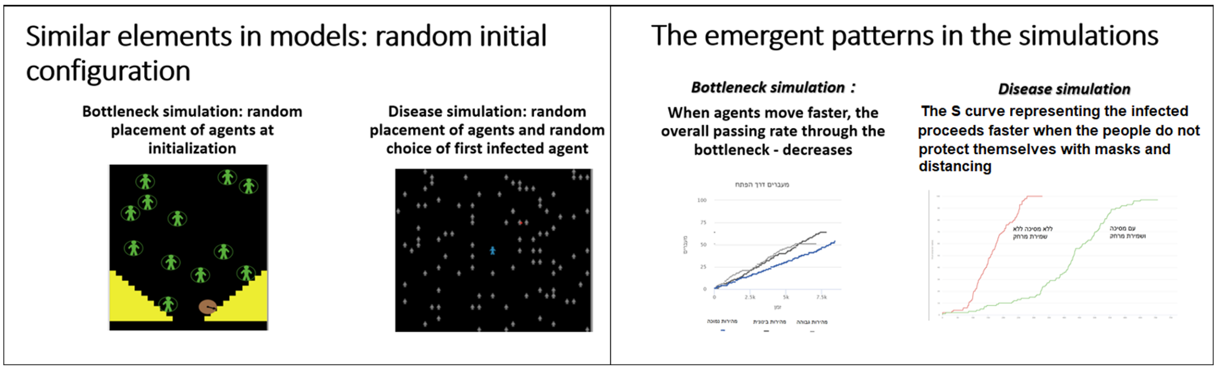

FIGURE 6
Slides presented after interacting with both the disease and the bottleneck simulations. The left slide mentions the random setup of both systems and right slide presents how parameters influence the emergent pattern in each simulation, as represented by the graphs of the overall passers through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

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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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EDITED BY
Christoph Kulgemeyer,
University of Bremen, Germany

REVIEWED BY
Alfonso Garcia De La Vega,
Autonomous University of Madrid, Spain
Marc De Vries,
Delft University of Technology, Netherlands

*CORRESPONDENCE
Jaime L. Sabel
✉ jlsabel@memphis.edu

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Investigating undergraduate students' engagement in systems thinking and modeling using causal maps

Jaime L. Sabel[1]*, Laura Zangori[2], Kathryn M. Parsley[3], Sedra Sous[1] and Jason Koontz[4]

[1]Department of Biological Sciences, College of Arts and Sciences, University of Memphis, Memphis, TN, United States, [2]Department of Learning, Teaching and Curriculum, College of Education and Human Development, University of Missouri, Columbia, MO, United States, [3]Donald Danforth Plant Science Center, St. Louis, MO, United States, [4]Department of Biology, Augustana College, Rock Island, IL, United States

Introduction: To develop a foundation of scientific understanding, undergraduate biology students need to integrate ideas about individual concepts into thinking about complex biological systems.

Methods: To investigate the extent to which undergraduate students engage in systems thinking, we conducted a pre-post study with students in a required undergraduate botany course at a small liberal arts college in the Midwest. All students in the study completed a causal map at the beginning and end of the course. Casual maps are similar to concept maps but demonstrate cause and effect relationships rather than other connections included in a concept map.

Results: Analysis showed that the majority of students did see some connections within the system but did not reach a high level of systems thinking.

Discussion: This work highlights the difficulties undergraduate students have with engaging in systems thinking but provides important insight into the particular areas in which students do engage in more complex thinking and areas in which we can specifically target with instruction and intervention.

KEYWORDS

systems thinking, ecosystems, undergraduate biology, causal maps, botany

Introduction

To develop a foundation of scientific understanding, undergraduate biology students need to understand causal interactions within biological systems. This need is highlighted in *Vision and Change* (AAAS, 2011). Specifically, within the biological sciences, undergraduate students should develop understanding of "complex biological processes through an elucidation of the dynamic interactions among components of a system at multiple functional scales" (AAAS, 2011, p. 13). Developing a system dynamics perspective occurs through asking students to use complex causal reasoning to understand how interconnected components occur within the system (Mehren et al., 2018; Verhoeff et al., 2018; Mambrey et al., 2020). When students are able to make these connections, then they are able to conceptualize causal effects as both linear, non-linear, and separated by time and space (Jacobson, 2001).

According to Momsen et al. (2022), there is an "implicit understanding that 'system' encompasses both the entities it comprises and the operational rules that govern how these entities interact." (p. 2). Systems thinking is the ability to understand how systems work and how changes in a system affect the other parts of the system (Evagorou et al., 2009; NRC, 2011; Momsen et al., 2022). Helping students engage in systems thinking is needed because thinking about systems is a fundamental aspect of understanding biology more broadly (Momsen et al., 2022). As thinking about systems requires understanding causal relationships, causal reasoning is also an important skill for students to master. In addition to highlighting Systems as a Core Concept, *Vision and Change* (AAAS, 2011) calls for a Core Competency of Ability to Use Modeling and Simulation. Modeling is one of the tools scientists use to describe living systems (AAAS, 2011). Therefore, supporting students to use modeling can help them to engage in thinking about thinking and develop both a Core Competency and a Core Concept (AAAS, 2011).

To investigate the extent to which undergraduate students build a system dynamic perspective, we used the causal map models they developed at the beginning and end of a botany course at a small liberal arts college as pre/post measures. We asked the following research questions:

1. To what extent do undergraduate students engage in systems thinking about an ecosystem?
2. How do undergraduate students reason about the causal relationships within an ecosystem?
3. What factors do undergraduate students prioritize when they consider causal relationships within an ecosystem?

Literature review

Ecosystem dynamics

The goal of our work is to support students in developing systems thinking about socio-ecological systems (SES). SES "seeks to overcome the dichotomy between natural and social systems by viewing the interrelationship between society and nature as a system in its overall context" (Mehren et al., 2018, p. 688). While ecosystems are frequently taught in K-12 instruction and course foci within undergraduate instruction, embedding frameworks to include SES within the classroom is rare (Sterk et al., 2017; Mehren et al., 2018). Overall, there are few studies that consider the complexity of undergraduate students' causal reasoning about SES (Davis and Stroink, 2016; Sabel et al., 2017). Yet, understanding the interrelationship between societal systems and ecosystems is crucial as "human actions transform ecosystems with consequences for human livelihoods, vulnerability, and security" (Sterk et al., 2017, p. 109). This concern is particularly salient when considering plant life.

Plants are the foundation of all life on Earth, so it is critical that students understand the criticality of plants within ecosystems as well as SES. Yet, there are few studies that explore if and how undergraduate students causally reason about plant function (e.g., Zangori and Koontz, 2017; Busta and Russo, 2020) and we could not locate studies that explore how undergraduate students causally reason about plants in SES. For these reasons, this study takes place within a botany course. The course focus was supporting undergraduate students in understanding the plant as a system as well as a critical component of ecological and societal systems.

An important part of considering relationships within ecosystems is reasoning about causes and effects. Causal reasoning occurs as students are able to link the components together within the system to realize causal patterns that span time and space. We draw on an ecological literacy framework proposed by Jordan et al. (2009) which is intended to build students' causal reasoning through three elements:

- *Ecological links*: understanding interrelationships between ecosystem systems and process.
- *Human links:* understanding human and human social systems interrelationships within the ecosystem.
- *Ecological reasoning*: causal reasoning about socio-ecological systems.

The three elements (ecological links, human links, and ecological reasoning) build in causal complexity (Zangori and Cole, 2019). Ecological links are the initial element in which students express ecological relationships, for example recognizing causal relationships between flowers and bees. Human links are separated out from ecological links because emphasis within western schooling tends to be placed on a system boundary that separates humans from ecosystems. This boundary is called the "nature-culture divide" (Bang et al., 2012, p. 303) which can create a barrier to students realizing and reasoning about causal links across systems (Jacobson, 2001). However, being able to successfully consider causal interactions across time and space requires that students conceptualize all inputs into the ecosystem, which includes societal inputs. If ecosystems are taught without considering the interrelationship between ecosystems and societal systems, then students do not have adequate information with which to ecological reason which leads to increased difficulty in understanding how societal systems impact ecosystems and vice versa (Coyle, 2005).

For this reason, we consider the framework to be hierarchical with the top level of complexity as students' ability to causally reason about the connections between human societal systems, and ecosystems. Reasoning about causal patterns within these systems moves against the cognitive heuristics that students developed as part of their daily lives (Grotzer and Tutwiler, 2014). These heuristics are based on observation and experience in which students interpret cause and effect as simple and linear with centralized control. This is seen most prevalently within students' understanding of food webs where prey is food for predators while predators maintain control on ecosystem carrying capacity by eating prey (Perkins and Grotzer, 2005). Yet, this simplifies the causal mechanism as a linear relationship between predator and prey (which is easily visible) when the actual mechanism is much more complex and includes a web of relationships within the ecosystem. Other "hidden" causal mechanisms are also crucial to system behavior such as chemical processes through natural ecosystem processes (e.g., photosynthesis, digestion, and biosynthesis) and anthropogenic processes (e.g., excess combustions, and photosynthesis reduction due to forest removal). If a student does not have the opportunity to make all of these processes visible to consider how these processes interact to form system behavior, then it is more challenging for students to build causal complexity (Bennett et al., 2020).

Modeling ecosystem dynamics

For students to consider the ecological and human links and obtain ecological reasoning, then they need a means to make the system components visible. We do this through modeling. Modeling is considered an epistemic practice of science as the act of modeling is central to the development of knowledge by both scientists as well as students' learning science (Gilbert, 2004). Modeling is a multi-phase process in which, first, students develop a model to answer a question or consider a problem about the causal relationships within a system. This initial model is a 2D diagrammatic model that is a mixture of drawing and writing developed from students' prior knowledge. Students are able to use this model to reason about the causal relationships within the system and articulate their answer or solution. In this manner, students are accessing and expressing their mental model of the system. The mental model serves as the building block for integrating new knowledge (Schultz et al., 2022). Students use this model as both a reasoning tool and as an evaluative tool to assess their own knowledge about system behavior. As they recognize reasoning gaps in their model, they seek out new ideas to build their conceptual understanding.

Because of our interest in students' ecological reasoning, we use a specific form of modeling called causal maps (Shin and Jeong, 2021) or within science education literature, referred to as socio-scientific models (Ke et al., 2020). Students create systems models, but the structure of the model forces students to focus on the links between components and use these links to convey causal relationships occurring across time and space within the system boundary (Schultz et al., 2022). This type of modeling is prevalent in other disciplines such as business (Montibeller and Belton, 2006), public health (Pronk and Faghy, 2022) and policy (Buchholz et al., 2007), but not widely used in science education (Ke et al., 2020). For example, Buchholz et al. (2007) created systems maps to assess the sustainability policies of bio-energy systems and recommend using causal mapping to understand and assess the societal and ecological impacts of bioenergy.

As seen from other disciplines, causal map modeling is relevant to socio-ecological systems as they "take social factors into consideration for the purposes of illustrating, explaining and predicting" causal factors within complex systems (Ke et al., 2020, p. 597). Modeling through causal maps is critical to building an understanding of system dynamics because students must consider how each component is causally connected to the scientific phenomenon, if the effect is immediate or delayed, where feedback loops occur within system elements, and if each factor is additive or reductive to the connecting factor (Richardson, 2011). The completed causal map models serve as a leverage for defining overall system behavior. Student construction and evaluation of causal maps have been embedded in secondary geography curriculum to support students systems thinking (Cox et al., 2018) and used to support secondary students' causal reasoning about evolutionary change (Hanisch and Eirdosh, 2021).

Methods

Context and participants

Our study took place over two semesters and included all students in an undergraduate botany course at a small Midwestern undergraduate liberal arts college. Thirty-eight students (100%) consented to participate in the first semester and 40 students (100%) consented to participate in the second. See Table 1 for demographic information. The course consisted of primarily junior-level (3rd year) undergraduate students, was required for all biology majors, and lasted ten weeks as the university operated under a trimester schedule. While the course was introductory in skill level and largely lecture-based, the professor also used a mixture of class discussion, the Socratic method, PowerPoints for students to add information to, worksheets, exposure to primary literature that also involved group activities, and debates that required preparation outside of the classroom. The topics covered included plant anatomy, morphology, physiology, and diversity. Basic ecology was a programmatic (departmental) mandate that was woven throughout the course. Course work included two-unit exams (consisting of a mix of multiple choice, fill-in-the-blank, drawing/labeling drawings, short answer, and short essay questions), class participation and assignments, a class discussion with worksheets and reflections on the book *Walden Warming* by Richard B. Primack, and a final exam. The final served as a third unit exam with an added section covering material from the entire course. Like the two-unit exams, the format was a mix of question types.

TABLE 1 Student demographic information.

Semester 1	Gender		Ethnicity	
	Man	10	Asian/Asian American	3
	Woman	26	Native Hawaiian, or Other Pacific Islander	1
			Hispanic, Latino, or Spanish origin	3
			White	29
Semester 2	Gender		Ethnicity	
	Agender	1	Another race/not listed	1
	Man	8	Asian/Asian American	3
	Woman	30	Black/African American	2
			Hispanic, Latino, or Spanish origin	6
			White	27

*Genders or ethnicities are not included in the list if no one identified in that category.

The course also required concurrent enrollment in a weekly, two-hour long botany lab, which constituted 20% of the overall grade in the course and included three lab quizzes and an inquiry-based research project. The lab content closely followed the topics covered in class. The research project lasted the entire semester. Students chose a common garden plant with short germination time (e.g., radish, broccoli, turnip, tomato, white clover, lettuce) and designed and conducted a controlled experiment testing an ecological issue (e.g., amount of water, intensity of light, amount of fertilizer, kind of fertilizer, exposure to UV light, exposure to acid rain, etc.). In addition to the control group, students were required to have three treatment levels of the independent variable. Students worked in teams of four and wrote sections that ultimately were put together in a PowerPoint poster as if they were going to present it at a professional meeting. This study was intended to determine whether students develop systems thinking during a class that discussed many aspects of systems thinking but did not provide specific instruction on how to think about systems or causal relationships among various aspects of systems. In this way, we were examining a "business as usual" course. Future work will focus on more directed instruction on both systems thinking and consideration of causal relationships.

Causal map assignment

To develop a scaffold to support students in systems thinking, we used the FRAMER scaffold design framework (Sabel, 2020). In the first semester, we assigned a causal mapping activity before and after the semester took place. Causal maps are a type of concept map but instead of writing a word to describe the relationship on the connection between concepts, students write a plus or minus sign to indicate whether the causal relationship is positive or negative (i.e., it is increased or decreased). We instructed students how to construct a causal map via a handout and gave them a picture of an environment very similar to their own. Students were instructed to base their causal map on the environment picture. We did not administer any extra instructions beyond what a causal map was and how to make one.

In the second semester, we included a short activity published by the Institute of Play (2020). The activity included a definition of a system and various characteristics of systems that students could use to better understand how to model a system with their causal maps. After the activity was introduced, the students completed their causal maps in the same manner as the first semester, with the same model environment picture.

To assist students in building their causal map with a particular environment in mind, we included a picture of an environment that included objects like crops, a farmer, a cow, a factory, water, etc. (see Figure 1). The prompt for the causal maps was, "What roles do plants play in the environment shown?" Students answered this by drawing a causal map of their own about the environment described above. The entire assignment is included in Appendix A.

Students were also asked to answer two questions about their causal map: (1) explain how your causal map demonstrates the relationships of plants and the environment? and (2) if someone, a non-scientist, asked you to explain how plants connect to everyday life or situations, how would you answer using your causal map?

FIGURE 1
Picture of an environment students were asked to consider for development of their causal maps.

Data analysis

The maps were coded using a rubric developed specifically for this study. The rubric was developed using an ecological framework (Jordan et al., 2009) and a systems reasoning framework (Hokayem and Gotwals, 2016). We chose these frameworks and adapted them to our rubric specifically because we wanted to take both an ecological and a systems approach to see how much students know about plants and their role in the environment. Using these frameworks, we developed a rubric based on the factors we saw in the causal maps. The rubric included five scoring criteria: plant links, human links, ecosystem links, causal reasoning, and systems reasoning. All of the criteria had a range of 0 to 3, 0 being the lowest score and 3 being the highest. See Appendix B for the entire rubric.

When assessing the criterion plant links, we considered the presence or absence of plants as a part of the requirement, as well as the presence or absence of both producer/consumer and photosynthetic relationships involving plants. For human links, we focused on whether or not humans were included, as well as how humans were integrated into the map using multiple relationships. For ecosystem links, we focused on whether or not students used both abiotic and biotic factors in their maps equally. For causal reasoning, we considered whether students included a causal relationship on every connection they indicated, and if so, how correct those relationships were. For systems reasoning, we evaluated the level of interconnectivity of the map, as well as a clear flow of ideas and the presence of one or more causal loops. Two authors completed multiple rounds of co-scoring and rubric revision on ten of the student responses (13% of total maps), until we reached an instrument that fully captured the students' responses, and we obtained a high interrater reliability (86% agreement). We then scored an additional ten student responses reaching a total of 20 dual-coded causal maps (26% of total maps) and reached 100% agreement following discussion. The first author then completed the remaining scoring alone which consisted of 18 causal maps from semester one, and 40 causal maps from semester two.

We coded all the causal maps according to our rubric and took averages for each criterion in the rubric, as well as an overall score for how well students did by adding the score on each criterion together. The highest score possible was 15 and the lowest score possible was zero. With that data, we completed a one-way repeated measures ANOVA to determine if there was a significant difference between pre and post scores. We repeated this process for both semesters and compared pre-test answers using an Independent Samples T-test to determine equivalency of scores between both semesters before causal maps were administered. We completed a second Independent Samples T-test to compare post-test scores among the 2 semesters to determine if the group with the scaffold in the second semester performed better than the group in the previous semester.

To evaluate the questions students answered after drawing their causal maps we began with the framework for systems thinking developed by Mehren et al. (2018) as utilized by Mambrey et al. (2020). This framework is defined by three stages of progress toward developing skills of systems thinking. We used qualitative open coding to determine if we could identify a similar type of hierarchy regarding systems thinking in their responses. To do this, we first identified whether or not students identified cause-and-effect relationships and feedback loops. We found a clear connection between recognizing systems relationships with the extent to which students included and described their feedback loops. We were able to determine three stages based on how students (1) identified simple cause and effect relationships, (2) identified multiple different cause and effect relationships within the system, or (3) noted multiple complex relationships within the system while including multiple feedback loops. See Table 2 for the stages of systems thinking we identified in the written responses.

In Stage 1 for Mehren et al. (2018) students "identified a low number of elements and relations mainly isolated or monocausal and as a vague set of relationships." In comparison, in our Stage 1, students only identify minimal cause and effect relationships within the system. In Stage 2 for Mehren et al. (2018), "the student is able to identify moderate number of elements and relations and they are mainly linear." This is similar to what we found in our data: students identified a moderate number of cause-and-effect relationships within a system but included little to no feedback loops. Finally, Stage 3 for Mehren et al. (2018) was reached when a "student was able to identify a high number of elements and relations and they were mainly complex and highly differentiated sets of relationships and as part of nested systems." In our scale, students scored as Stage 3 when they were able to identify multiple complex relationships within the system and be able to identify multiple feedback loops.

Results

Causal map scores

We used one-way repeated measures ANOVA to analyze the changes in causal map rubric scores and found that the only aspect of the causal maps that students improved upon over the semester was using Ecosystem links ($p < 0.05$). This indicates that students did not improve their abilities to use causal maps to explain their views on plants and their role in the environment, except for with ecosystem links. See Table 3 for results from the first semester and Table 4 for the results from the second semester. Note that the pre to post difference in the scores for Ecosystem links was only significant in the first semester, but not in the second semester.

An Independent Samples *T*-test indicated few differences in pre or post scores between the first and second semesters. For the pre-test, first semester scores were significantly higher than second semester scores for Causal Reasoning and Explanation to non-scientists (Table 5). However, we saw no significant differences in any categories when we compared the post-tests between the first and second semesters (Table 6).

Because a significant difference in Ecosystem links occurred only in one semester and differences between the semesters were limited to two categories in the pre-test, but not the post-test, we conclude that the trends indicate no real differences between pre and post or between the first and second semesters.

Focus on human links

To further examine what students included in their causal maps, we chose the category of human links. This category was not significantly different from pre to post, however, we found it interesting how few students included contributions from humans in their causal maps even though a human, and human-related items (factory, car, etc.) were included in the picture students were shown. Figure 2 shows the distribution of causal map scores across all assignments in both semesters. Most students fell into the score categories of 1 and 2 in all the assignments indicating most included some aspect of how humans interact with the environment, but most did not to a high degree.

In the first semester, we found that five students fell above and five students fell below one standard deviation of the mean for the

TABLE 2 Stages of understanding of systems thinking.

Stages	Descriptions
Stage 1	Provides a vague level of understanding when trying to comprehend the importance of causal maps.
Stage 2	Makes moderate connections between plants and the environment but does not emphasize specific examples to create broader connections.
Stage 3	Identifies multiple different connections relating to plants and the environment, these connections are complex and identify multiple different examples.

TABLE 3 Pre/post causal map scores for semester 1.

Test	Pre-mean	Post mean	*F* value	*p*
CM overall	10.03	10.36	0.231	0.634
Plants	1.17	1.31	0.263	0.611
Humans	1.25	1.28	0.036	0.851
Ecosystem	1.28	1.67	5.514	0.025*
Causal reasoning	1.31	1.36	0.139	0.711
Systems reasoning	0.97	1.03	0.139	0.711
Explanation	1.25	1.14	0.302	0.586
Correctness	1.00	1.06	0.085	0.773
Non-scientist	1.81	1.53	0.907	0.348

TABLE 4 Pre/post causal map scores for semester 2.

Test	Mean 1	Mean 2	*F*	*p*
Plant links	1.55	1.60	0.051	0.822
Human links	1.525	1.625	0.394	0.534
Ecosystem	1.425	4.65	1.491	0.229
Causal reasoning	0.850	0.975	0.526	0.473
Systems reasoning	0.95	1.225	2.951	0.094
Explanation of map	1.33	1.15	0.923	0.343
Scientific correctness of explanation	1.21	0.871	2.398	0.130
Explanation to non-scientist	1.231	1.128	0.291	0.593
Total score	9.675	10.325	0.943	0.338

TABLE 5 Comparison of pre-test causal map scores between semester 1 and 2.

Test	Levene's pass?	N CM1	N CM2	Mean CM1	Mean CM2	*T*	*p*
Plant links	0.336, yes	38	40	1.16	1.55	−1.487	0.141
Human links	0.324, yes	38	40	1.21	1.53	−1.642	0.105
Eco links	0.316, yes	38	40	1.32	1.43	−0.620	0.537
Causal reasoning	0.186, yes	38	40	1.26	0.85	2.790	0.007*
Systems reasoning	0.084, yes	38	40	1.0	0.95	0.290	0.772
Explanation of map	0.736, yes	38	39	1.26	1.33	−0.284	0.777
Scientific correctness	0.074, yes	38	39	1.0	1.21	−0.786	0.434
Explanation to nonscientist	0.384, yes	38	39	1.82	1.23	2.445	0.017*
Total scores	0.207, yes	38	40	10.03	9.68	0.447	0.656

TABLE 6 Comparison of post-test causal map scores between semester 1 and 2.

Test	Levene's pass?	N CM1	N CM2	Mean CM1	Mean CM2	*T*	*p*
Plant links	0.062, yes	36	40	1.31	1.60	−1.085	0.281
Human links	0.137, yes	36	40	1.28	1.63	−1.865	0.066
Eco links	0.510, yes	36	40	1.67	1.65	0.076	0.939
Causal reasoning	0.920, yes	36	40	1.36	0.98	1.878	0.064
Systems reasoning	0.008. no	36	40	1.03	1.23	−1.056	0.295
Explanation of map	0.933, yes	36	40	1.14	1.15	−0.05	0.960
Scientific correctness	0.474, yes	36	40	1.06	0.93	0.590	0.557
Explanation to nonscientist	<0.001, no	36	40	1.53	1.18	1.149	0.255
Total scores	0.881	36	40	10.36	10.33	0.045	0.965

pretest. Of the 26 students who were within 1 standard deviation of the mean, 12 were above it and 14 were below it. A high scoring map completed by a student who received a 12 out of a possible 15 points overall for their second map in the course connected plants to both food and photosynthesis; included humans as a connection to oxygen, carbon, and food; included approximately equal numbers of both biotic and abiotic factors in their map; indicated clear and correct causal relationships; and had a highly interconnected map with nested causal loops as a central figure. However, another student received a 1 out of 15 on their causal map. One reason for this is that the student likely did not understand the point of the exercise as they primarily referred to photosynthesis in their map, but they also did not specifically talk about plants at all. They did not include humans in their map, all of their ecosystem factors were abiotic, they indicated no causal relationships on their map, and all of the relationships considered on the map were linear and not at all interconnected.

Figure 3 shows examples of causal maps that received each level of scoring.

Score of 0. In Figure 3A, the student did not refer to "humans," or, "people," and did not include any type of concept that is directly related to or caused by humans. Every other item on the map is something found in nature and not focused on humans in a socioscientific context.

Score of 1. In Figure 3B, the student included components such as, "factories," "cars," "pollution," "agriculture," and even, "jobs" which are all concepts relating to what humans do in an environment. However, this student did not actually use the word, "humans," or, "people," in their map either, despite the fact that many of the concepts included in the map are directly caused by humans in a socioscientific context.

Score of 2. In Figure 3C, the student included the word, "humans," in their pre-test map, however, humans have only one connection to the rest of the map and are largely separated from all of the other elements appearing in the map. Additionally, the word, "humans," is only connected to the word, "oxygen," which is not a concept directly caused by humans in a socioscientific context.

Score of 3. In Figure 3D, the student included the word, "people," but also included several connections between, "people," and other elements of the map. There are seven total connections between the element, "people," and other concepts in the map. Of those seven, three can be thought of as concepts directly caused by humans in a socioscientific context. "People" is connected to "cars," "gas," and "factory pollution," all of which are related to human impacts on the environment. The other four elements connected to the term, "people," are "oxygen," "cows/livestock," "energy production," and "produces O_2 and CO_2 to help balance [the] environment," which is the central idea of the map. These connections point to an understanding of how

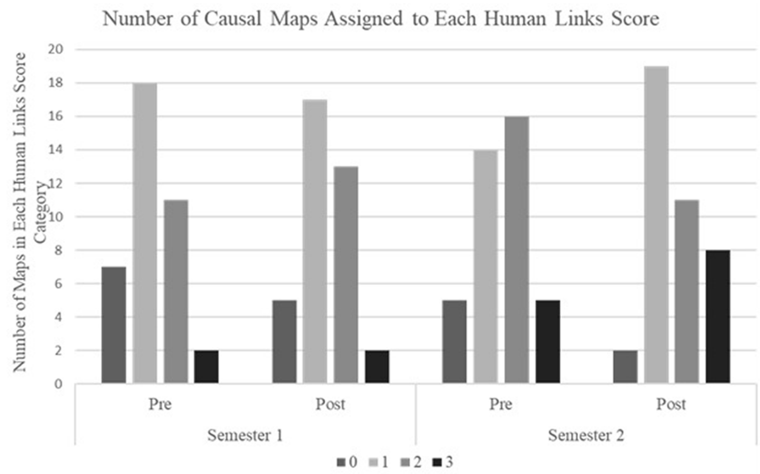

FIGURE 2
Number of causal maps assigned to each human links score category.

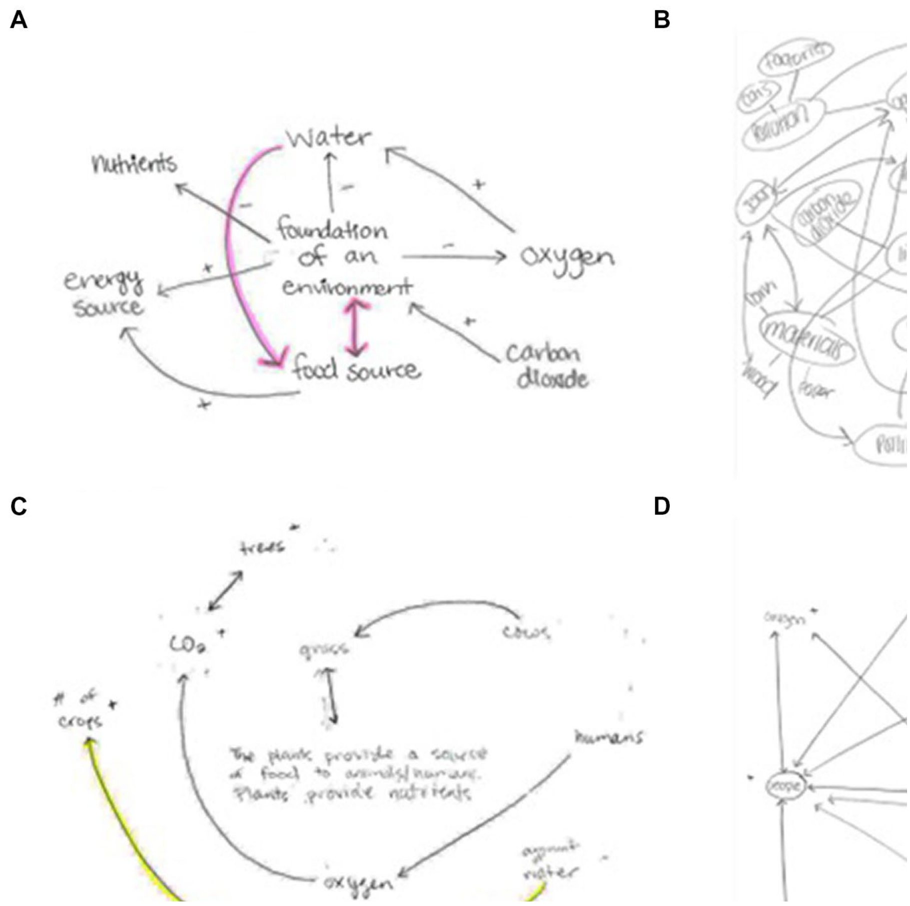

FIGURE 3
Examples of each level of causal map scoring. **(A)** Score of 0. No mention of humans or any human-caused phenomena. (Participant 11, pre-test causal map). **(B)** Score of 1. Human-caused phenomena (e.g., agriculture, pollution, wind energy) are mentioned, but humans are not. (Participant 8, post-test causal map). **(C)** Score of 2. Humans are mentioned on the map but are isolated from the other ideas present. (Participant 40, pre-test causal map). **(D)** Score of 3. Humans are present and so are human-caused phenomena (e.g., cars, gas, factory pollution) and humans are highly connected with the rest of the ideas on the map, as well as the human-caused phenomena. (Participant 12, pre-test causal map).

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humans are dependent upon plants for oxygen, and how we have domesticated cows for agricultural use.

Written answers to questions

To analyze students' systems thinking understanding and level of use in the answers to the questions about their causal maps, we developed a modified scale using the chart of *Skills of Systems Thinking* developed by Mehren et al. (2018) and as utilized by Mambrey et al. (2020). Qualitative analysis revealed three levels of systems thinking within students' answers to the questions (see Table 2). At Stage 1, students provided a vague level of understanding when trying to comprehend the benefit of drawing causal maps. At Stage 2, students made moderate connections between plants and the environment but did not elaborate with specific examples that would help them to create broader connections. At Stage 3, students identified multiple different connections relating to plants and the environment. These connections were complex and identified specific examples.

Question 1. In Question 1, students were asked to "Explain how your causal map demonstrates the relationships of plants and the environment." Students were asked to answer this question about both their pre-class and post-class causal maps. Analysis of Pre-Question 1 showed that 21 out of the 40 students fell into Stage 2 of the level of utilizing systems thinking regarding explaining their causal maps (Table 7). This conveys that students were only making moderate or broad connections when attempting to demonstrate the relationships between plants and the environment. For example, one student said "Plants help to reduce emissions in this environment. It shows that pollution, cars, structure, electricity, etc. add problems for plants to clean up" (Student 24).

This is considerably more complex than a student who scored in Stage 1 who simply said, "Plants allow for survival" (Student 4). The response given by this student shows a vague level of understanding when making connections between plants and the environment. Students who scored in Stage 3 wrote a well-developed answer that made use of specific connections between plants and the environment. For example:

> My causal map demonstrates the interconnected relationships that plants have within the environment. Plants use CO_2 (product of many living things) to produce O_2 (necessity of many living things). Taking in CO_2 in a large amount can be considered a carbon sink, returning the carbon from the air back into the ground. Not only do plants produce CO_2, but they also create habitats for living things and produce resources living things can use (wood, food, etc.). Agriculture plays a big role in the production of food for humans, but with this, both positive and negative effects occur. Over usage of land results in desertification. Over usage of fertilizers results in runoff and dead zones, negatively impacting surrounding ecosystems. Agriculture allows humans to have time to do other things besides hunting and gathering (the old way of collecting food) showing a positive impact. Plants play a larger role in everyday life, one that many do not realize (Student 38).

This response makes several connections between the positive and negative impacts on the relationship between plants and the environment. Of note, all Stage 3 responses were much longer and contained more details than either Stage 1 or Stage 2 responses.

TABLE 7 Scores in each stage for each question.

	Pre-Q1	Post-Q1	Pre-Q2	Post-Q2
Stage 1	13	17	13	14
Stage 2	21	16	19	19
Stage 3	6	7	8	7

When this question was administered again at the end of the semester, results showed the majority of students falling in Stage 1 (17 out of 40) and Stage 2 (16 out of 40) (Table 7). Students showed minimal improvement, or no improvement at all, in their responses between the pre-class and post-class assignments.

Question 2. In Question 2, students were asked "If someone, a non-scientist, asked you to explain how plants connect to everyday life or situations, how would you answer using your causal map?." Analyzing the results from Pre-Question 2 showed that, as with Pre-Question 1, 19 out of 40 students fell in the Stage 2 category (Table 7). For example, a student who scored in Stage 2 wrote, "Without plants we would not have air, a lot of shelter comes from trees, food, etc. Plants are necessary for survival" (Student 4). This student expressed why plants are important and the different components we gain from them but did not rank in Stage 3 because they did not draw specific connections to everyday life.

A student who scored in Stage 1 wrote, "It represents how so many different factors in the environment can be correlated and have an impact within society" (Student 14). This student scored in Stage 1 because, although they mentioned that many different components are related, they did not include specific factors and how those factors impact the environment.

Analysis of answers to Post-Question 2 exhibit nearly the same results as Pre-Question 1, most students scored as Stage 2. We did not see an enhancement in the development of the responses from the pre-class to the post-class assignment. For example, a student who ranked at Stage 2 for Pre-Question 2 stated, "My causal map shows how plants help maintain the lives of all living organisms and how everything feeds off each other. Plants feed off the CO_2 that humans produce, and humans feed off all of the benefits plants give us" (Student 40). When asked the same question again in Post-Question 2 the student stated, "My causal map shows how humans can use plants in many different ways. We need them because they produce oxygen for us, food, shelter, medicine, and many other things without plants it would be very difficult for us to exist," and again scored in Stage 2.

In both Pre- and Post-question 2, few students scored in the Stage 3 level of drawing connections (eight out of 40 for Pre-Question 2 and seven out of 40 for Post-Question 2) (Table 7). A Stage 3 answer requires multiple connections between plants and the environment and would thoroughly explain how those connections are important. A student who scored in Stage 3 for Post-Question 2 stated,

> My causal map would show them what plants do for every day like through the simple points made in the causal map. The plant provides oxygen, income, food, oxygen, and consumes CO_2. The oxygen, income, food, and sustainability of life are where we receive from plants while CO_2 is what is removed. CO_2 emission affects the amount of oxygen made and the amount of cash crops (food) affects income" (Student 21).

We found little to no improvement in regard to drawing more in-depth connections within the environment. For example, a student who scored in Stage 1 for Pre-Question 2 states, "They're need[ed] for survival because you need O_2 to breathe and need to live off of it" (Student 10). When asked again in Post-Question 2, the students wrote "We need them to breathe and eat and make money. They're essential for us to live," which again scored in Stage 1. Because we saw 21 out of 40 students scoring in the Stage 2 category, we can conclude that many students tend to make broad connections rather than making specific connections with a variety of different components.

Next, we analyzed the extent to which students changed stages in their answers to the questions between the pre- and post-assignments. We saw students who improved to a higher stage, remained at the same stage, and who regressed to a lower stage. For Pre- to Post-Question 1 we found that a total of nine students improved, 20 were unvarying, and ten regressed (Table 8). For Pre- to Post-Question 2, eight improved, 22 remained the same, and nine regressed (Table 8).

As shown in Figure 4, of the students who were categorized in Stage 1 for Pre-Q1, five improved to Stage 2, while seven stayed at Stage 1 in their answer to Post-Q1. No students scoring in Stage 1 for Pre-Q1 increased to Stage 3 in Post-Q1. For students placed in Stage 2 for Pre-Q1 we found that four improved to Stage 3, ten remained at Stage 2, and seven regressed to Stage 1 when answering Post-Q1. Finally, of the students placed in the Stage 3 category for Pre-Q1, three remained in Stage 3 while three regressed down to Stage 1 when answering Post-Q1. We attribute this last regression to students not taking the second assignment as seriously as the first.

As shown in Figure 5, of the students who were categorized in Stage 1 for Pre-Q2, five improved to Stage 2 and seven remained at Stage 1 in their answers to Post-Q2. As with Question 1, no students who scored in Stage 1 increased to Stage 3. For students categorized as Stage 2, three improved to Stage 3, ten remained in Stage 2, and six regressed to Stage 1 for Post-Q2. Lastly, of the students in the Stage 3 category, four remained in Stage 3 while three regressed to Stage 2 and one regressed to Stage 1 for Post-Q2.

TABLE 8 Pre- and post-assignment totals for question 1 and 2.

	Improved	Remained	Regressed
Q1	9	20	10
Q2	8	22	9

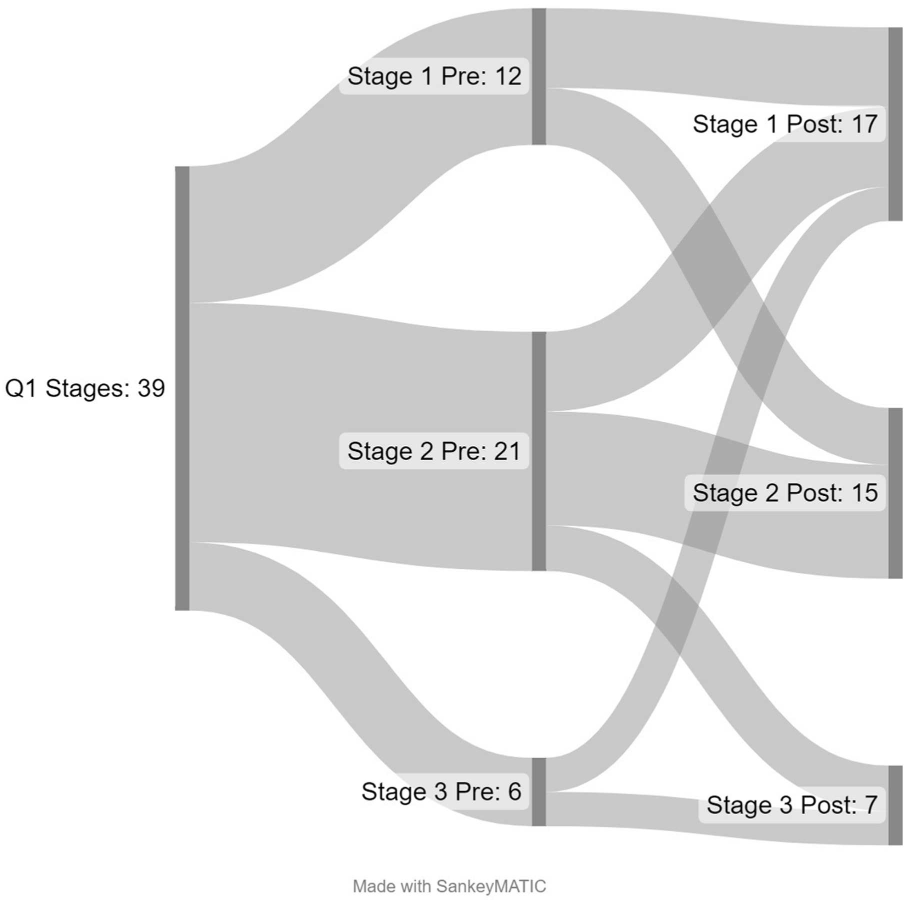

FIGURE 4
Analysis of the number of students who improved to a higher score, remained at the same score, or regressed to a lower score between the Pre- and Post-answers to Question 1.

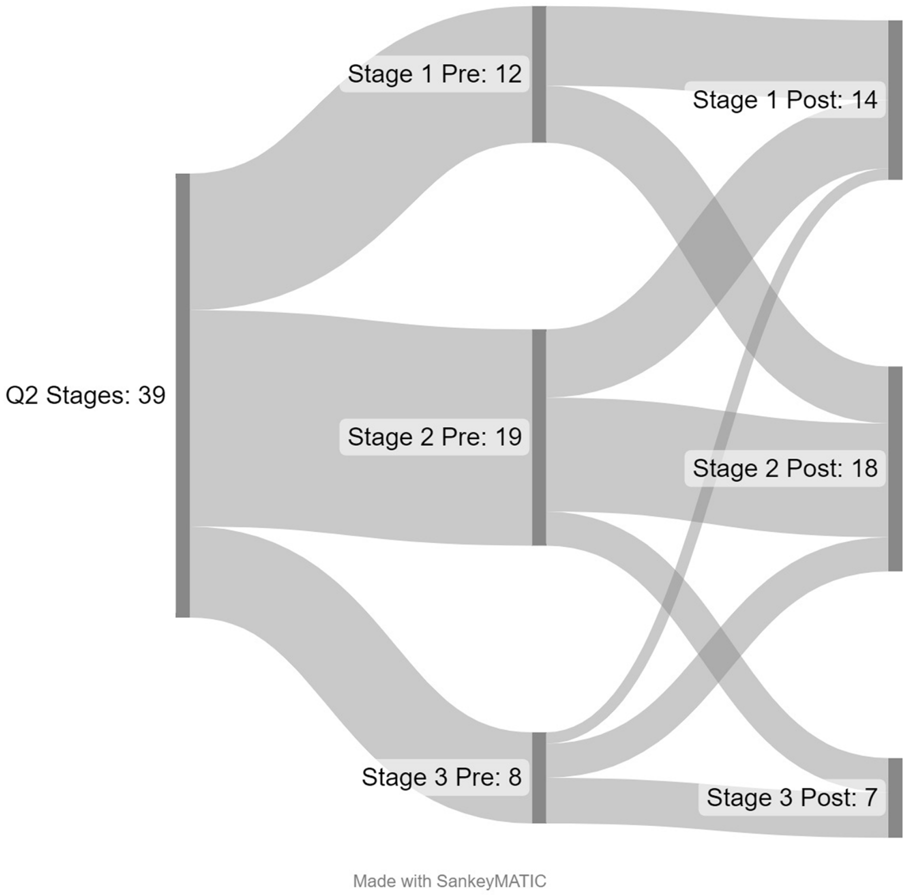

FIGURE 5
Analysis of the number of students who improved to a higher score, remained at the same score, or regressed to a lower score between the Pre- and Post-assignments for Question 2.

Discussion

Undergraduate biology programs should include opportunities for students to engage in complex biological processes and causal reasoning to understand how interconnected components are necessary for systems to function linearly, non-linearly, and across time and space (Jacobson, 2001; Evagorou et al., 2009; AAAS, 2011; NRC, 2011; Mehren et al., 2018; Verhoeff et al., 2018; Mambrey et al., 2020). Thinking about systems requires students to both understand that a system is both the entity and how the entities interact (Momsen et al., 2022). While the term "ecosystem" is often taught across the K-16 spectrum, it is rarely done so without systems thinking, particularly with how natural and social systems are intricately linked (Mehren et al., 2018; Sterk et al., 2017). Further, little work has focused on how undergraduate students engage in causal reasoning socio-ecological systems (Davis and Stroink, 2016; Sabel et al., 2017).

Vision and Change (AAAS, 2011) included Systems as one of the five Core Concepts and Modeling and Simulation as a Core Competency. Modeling is an important part of the development and integration of scientific knowledge (Gilbert, 2004; Schultz et al., 2022). Integrating modeling with systems thinking requires students to also develop causal reasoning. This, too, is challenging for students because of the difficulty in considering both natural and societal aspects of systems such as ecosystems (Jacobson, 2001; Coyle, 2005; Jordan et al., 2009; Bang et al., 2012; Zangori and Cole, 2019). Our focus on ecosystems in this study is, in part, because of this interaction between nature and society. In addition, little research has focused on how students reason about plant function and how plants are a crucial part of ecosystems (e.g., Zangori and Koontz, 2017; Busta and Russo, 2020; Parsley et al., 2022).

In this study, we focused on the use of causal maps as a form of modeling causal relationships within ecosystems (Shin and Jeong, 2021). Although causal modeling has been used in other disciplines (Montibeller and Belton, 2006; Buchholz et al., 2007; Pronk and Faghy, 2022), they have been only limitedly utilized in science education (e.g., Cox et al., 2018; Ke et al., 2020; Hanisch and Eirdosh, 2021). This focus on causal relationships is not something that students typically consider in their daily lives beyond linear reasoning such as in food webs (Perkins and Grotzer, 2005; Grotzer and Tutwiler, 2014). Therefore, it is important for students to have exposure to causal complexity such as feedback loops for them to develop causal reasoning and systems thinking skills (Richardson, 2011; Bennett et al., 2020).

In our first research question, we asked "To what extent do undergraduate students engage in systems thinking about an ecosystem?" We found that the majority of students fell into mid-range scores meaning they did see some connections within the system but did not reach a high level of systems thinking. We did not see an improvement in the causal maps from pre to post except among ecosystem links and then only in the first semester. One reason for this result may be that students did not have prior experience with using causal maps and may not yet have had the skills necessary to demonstrate connections. While they may have recognized part of the system, it seems they did not fully consider the system itself or how the entities interact (Momsen et al., 2022). It seems students also exhibited the difficulty in merging both natural and society aspects of the ecosystem they were asked to analyze as previously described (e.g., Jacobson, 2001; Coyle, 2005; Jordan et al., 2009; Bang et al., 2012; Zangori and Cole, 2019). Therefore, future work will need to focus on providing more foundational work on thinking about systems both as a whole and as the entities that make up the whole, as well as considering both natural and societal impacts on the system.

In our second research question, we asked "How do undergraduate students reason about the causal relationships within an ecosystem?" The only significant difference we found in the causal reasoning category was between the pre-tests of semester 1 and semester 2. This indicated there may have been a difference in how students came into the class thinking about causal relationships, but it did not last from pre- to post-assignment in a single semester. In the written responses to the questions accompanying the causal maps, we also saw little usage of feedback loops or connections that went beyond simple, linear relationships. Again, this aligns with previous work that has shown it is rare that students consider causal relationships beyond linear reasoning (Perkins and Grotzer, 2005; Grotzer and Tutwiler, 2014). Future work will need to focus on how to engage students in reasoning that will allow them to consider complexity in relationships in ways that are non-linear and that span time and space (Jacobson, 2001; Evagorou et al., 2009; AAAS, 2011; NRC, 2011; Mehren et al., 2018; Verhoeff et al., 2018; Mambrey et al., 2020).

In our third research question, we asked "What factors do undergraduate students prioritize when they consider causal relationships within an ecosystem?" We found little consistency in what students considered beyond including the basic features found in the ecosystem picture they were given with the assignment and topics they had previously learned were associated with plants and ecosystems (i.e., photosynthesis). However, although humans and human-related factors were included in the assignment picture, few students included human-related causes and effects in their causal maps or in the answers to the questions following the causal maps. Again, this points to the difficulty students have with considering both natural and societal aspects within systems (Jacobson, 2001; Coyle, 2005; Jordan et al., 2009; Bang et al., 2012; Zangori and Cole, 2019). Future work will need to focus on how to help students understand the multiple factors involved in systems thinking.

Overall, our work has further shown many of the aspects of systems thinking that were already known. However, we have expanded that knowledge to include undergraduate biology students. We show that the problems with systems thinking observed in K-12 students persist into undergraduate courses. This highlights the importance of prioritizing thinking about systems in undergraduate education, particularly as it has been identified as a Core Concept of biology (AAAS, 2011). While the use of a causal map assignment did not significantly improve students' engagement in systems thinking, this study did help us to better understand the particular challenges we need to address to better support undergraduate students in both the Core Concept of Systems and the Core Competency of Modeling (AAAS, 2011). This study was intended as a pilot to determine whether students develop systems thinking during a class that discussed many aspects of systems thinking but did not provide specific instruction on how to think about systems or causal relationships among various aspects of systems. Therefore, we did not expect students to improve dramatically, however, we were still surprised by the consistent lack of improvement given consideration of systems (even though not systems thinking) in the course. Future work will focus on more directed instruction on both systems thinking and consideration of causal relationships.

This study is limited because of the small sample size within the botany course and limited time within the semester to complete the study and administer the causal maps. However, it has important implications for undergraduate biology instructors as they consider how to teach students about botany topics either in stand-alone botany courses, or as part of general biology or ecology courses.

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 University of Memphis Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

Author contributions

JS, LZ, KP, and JK contributed to the conception and design of the study. JS, KP, and JK contributed to data collection. JS, KP and SS contributed to data analysis. JS, LZ, and KP wrote the manuscript. All authors contributed to the article and approved the submitted version.

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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.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2023.1159486/full#supplementary-material

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EDITED BY
Subramaniam Ramanathan,
Nanyang Technological University, Singapore

REVIEWED BY
Milan Kubiatko,
J. E. Purkyne University, Czechia
Chris Schaben,
University of Nebraska Omaha, United States

*CORRESPONDENCE
Tom Bielik
✉ tom.bielik@beitberl.ac.il

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Using concept maps to evaluate preservice biology teachers' conceptualization of COVID-19 as a complex phenomenon

Tom Bielik[1]*, Johannes Jagemann[2], Moritz Krell[3], Dirk Krüger[2] and Orit Ben Zvi Assaraf[4]

[1]Faculty of Education, Beit Berl College, Kfar Saba, Israel, [2]Department of Biology Didactics, Freie Universität, Berlin, Germany, [3]IPN-Leibniz Institute for Science and Mathematics Education, Kiel, Germany, [4]Department of Science and Technology Education, Ben Gurion University of the Negev, Beer Sheva, Israel

Introduction: The COVID-19 pandemic showed the critical importance of supporting teachers' and students' systems thinking when making sense of complex phenomena. This study sets to explore preservice biology teachers' (PBTs) mental models of COVID-19 as complex phenomenon using concept maps.

Methods: 27 PBTs concept maps of COVID-19 outbreak were collected and taken for analysis. Structural and complexity attributes were identified in participants' concept maps and the relationships between them were tested, providing statistical analyses using exemplary concept maps.

Results: The results suggest that the appearance of many concepts in a map (structural attribute) does not necessarily indicate high level of complexity, but rather the amount of simple structural relationships (complexity attribute). On the other hand, the results indicate that higher structural sophistication (e.g., high number of connections and junctions) could be associated with the complexity level of the map.

Discussion: This study provides a practical method for evaluating the complexity level of PBTs' systems thinking, suggests a possible link between structural and complexity attributes in their concept maps, and demonstrates the need to further support PBTs in developing their systems thinking skills in the context of complex biological phenomena.

KEYWORDS

systems thinking (ST), complexity, concept map (CM), COVID-19, preservice biology teachers

1. Introduction

In the modern world, people are exposed to a variety of phenomena, such as climate change, ozone depletion and rising carbon dioxide levels, which are characterized by a complex web of interactions. More recently, the COVID-19 pandemic, also known as the coronavirus pandemic, is an ongoing global pandemic of coronavirus disease 2019 (COVID-19), which is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This pandemic has upended the lives of all people across the globe (see Supplementary material 1 for summary World Health Organization, 2021 information about COVID-19 from the World Health

Organization). COVID-19 vaccines can help end the pandemic, but it's essential that everyone has access to them. It is also important to recognize that there are several scientific and non-scientific opponents for the COVID-19 vaccines who question the effectiveness and usefulness of the vaccination regimes adopted around the world. This requires the public and science students to be more aware of the different views, the scientific and non-scientific evidence that are available to support these views, and the complexity of information that should be considered when making decisions on this matter. This complexity cannot be fully understood and, hence, solved with the disciplinary tools or methodology that are commonly use, in which each variable is isolated and tested separately. Rather, it requires the development of an appropriate approach, which addresses such problems holistically, as an interconnected, complex system (Haley et al., 2021; Puig and Uskola, 2021)–a whole that is more than the sum of its parts (Jacobson and Wilensky, 2006). Uskola and Puig (2023) argued that the pandemic of COVID-19 has highlighted the need to develop a citizenry with skills to analyze complex socioscientific problems, in which systems thinking and futures thinking worked together, allowing students to make decisions and to be active citizens.

Capra and Luisi (2014) Systems View of Life portrays the twenty-first century as having inherited major problems involving the environment, energy, climate change, biosecurity, and financial security. They characterize these as systemic problems in that they are all connected. Capra's deep ecological view requires a "radically new conception of life" and a new understanding of how the world is changing. Capra and Luisi (2014), have asked for shifts in perceptions and ways of thinking understanding social–ecological systems as complex adaptive systems, especially at the level of the Earth System as a whole. This approach emphasized the systemic properties level that emerge from the underlying patterns of organization—suggesting that systems cannot be understood, nor their behavior predicted on the sole basis of information relating to their individual parts.

Understanding and analyzing such complex phenomena requires students to engage in "systems thinking"—a higher order thinking skill associated with the ability to understand how the behavior of complex systems is manifested at different scales (from the microscopic to the global/biospheric) and how patterns emerge from the interactions among system components (Gilissen et al., 2021). Rachmatullah and Wiebe (2021) suggested that given this broad definition of systems thinking, research in science education has identified many different types of thinking processes that fall under the umbrella of systems thinking, such as thinking in levels, causal reasoning, mechanistic reasoning, structure–function-behavior, dynamic thinking, cyclic thinking, and interdisciplinary thinking.

Complex systems are prevalent in many scientific fields, and at all scales—from the micro scale of a single cell (such as a human fertilized egg) to macro complex systems such as cities or ecosystems (Yoon et al., 2017). Systems are a central feature of biological sciences. Such systems are made up of many entities, reflecting the multiple levels of organization, and whose interactions emerge into distinct collective patterns (Verhoeff et al., 2018). Hmelo-Silver et al. (2000) defined the dynamic system as a coherent whole composed of multiple components working cooperatively both on a single level and between levels. Because of the dynamic nature of the connection between the system's different levels of hierarchy, complex systems are difficult to understand, even for experts (Hmelo-Silver and Azevedo, 2006). Recent review studies indicate that there are only few studies on science teachers and systems thinking (York et al., 2019; Bielik et al., 2023). further, little is known about (preservice) teachers' abilities to appreciate complex phenomena—such as the COVID-19 pandemic—as systems. Supplementary material 2 provides detailed description of the COVID-19 pandemic as complex system, using the eight system characteristics of Gilissen et al. (2020).

In biology education, the teaching of complex systems is further emphasized, since many complex biological systems also incorporate a variety of social, political, and cultural elements, which expand the boundaries of the system and add even more layers of complexity (de Sousa et al., 2019). One of the important questions that should be asked, in light of this issue, is: Are biology teachers able to grasp these issues well enough to convey them to their students?

This study addresses the above question by examining the systems thinking of preservice biology teachers (PBTs). Specifically, concept maps were used through which the PBTs were able to externalize their mental models of one of the most pertinent examples of a complex, socio-scientific system—the Coronavirus pandemic. Following this, both qualitative and quantitative analyses of PBTs' concept maps were performed in order to determine which characteristics of systems thinking were reflected in their visual representations. The goal in doing so was that the specific strengths and weaknesses revealed by their concept maps could be used as a basis for scaffolding strategies in future preservice education.

2. Theoretical background

2.1. Systems thinking

Systems thinking is widely acknowledged as an important component in science education, the development of which is necessary for helping students make sense of complex phenomena in biological systems (Verhoeff et al., 2018). As mentioned in the Next Generation Science Standards (NGSS Lead States, 2013) and stressed in Nordine and Lee (2021), systems and system models are a critical crosscutting concepts that K-12 science students are required to develop in order to make sense of phenomena. Researchers agree that this higher-order thinking skill provides students with a more coherent understanding of biology by revealing the universal principles that apply to biological systems on different biological levels of organization (Hmelo-Silver et al., 2017; Knippels and Waarlo, 2018; Mambrey et al., 2020). These universal principles, or "system characteristics," are generally divided into three different groups, which Yoon et al. (2018) summarize in their comprehensive review as (a) *structures*, referring to the components, the physical features of the system, (b) *processes*, referring to the dynamic interactions and mechanisms that fuel the evolution of complex systems, and (c) emergent *states*, which describes the systemic patterns and properties that govern how complex systems exist in the world.

While systems thinking is part of many science curricula or standard documents (e.g., KMK, 2005, 2019; NGSS Lead States, 2013), multiple definitions of systems thinking can be found in science education literature. The differences between the various models for assessing systems thinking are largely due to variations in how the precise characteristics of a complex system are defined, based on the specific scientific phenomena addressed in the respective studies.

Several models have been put forth as useful means of representing the various forms and levels of system thinking. One promising approach for portraying systems thinking in a way that reflects the system's multiple interacting components and their states is Structure-Behavior-Function (SBF) thinking (Hmelo-Silver et al., 2007). In SBF terms, the structure portion of an SBF model of a complex system specifies the "what" of the system, meaning the components of the system as well as the connections among them. Behaviors specify the "how" of the complex system, namely the causal processes occurring in it. Functions specify an understanding of the "why" of the system. The SBF model, has been recognized as useful for students' understanding of various biological systems, including human body systems (Hmelo-Silver et al., 2007; Gnidovec et al., 2020), and ecological systems (Jordan et al., 2014; Nesimyan-Agadi and Ben-Zvi Assaraf, 2021). Recently, Momsen et al. (2022) introduced the biology systems-thinking (BST) framework, which describes four levels of systems-thinking skills: (1) describing a system's structure and organization, (2) reasoning about relationships within the system, (3) reasoning about the system as a whole, and (4) analyzing how a system interacts with other systems. Each level of the BST is described using structure–relationship–function (SRF) language, where structures are the components that comprise the system; relationships are the mechanisms that explain how structures are related; taken together, structures and behaviors interact to result in a particular system function.

Hmelo-Silver et al. (2017) modified the SBF model, creating an alternative conceptual framework called Components-Mechanisms-Phenomena (CMP). This framework provides a representation of all the system's attributes, including the structures (components) within the system, the specific processes and interactions (mechanisms) that occur between them, and the macro scale of processes and patterns within a system—the phenomena. The refined conceptual representation was presented by Hmelo-Silver et al. (2017) and was later adopted by Snapir et al. (2017), reflecting the mechanistic reasoning of human body learning. Another form of conceptual representation is the Systems Thinking Hierarchy (STH) model developed by Ben Zvi Assaraf and Orion (2005). This model divides how people think about and understand complex systems according to eight hierarchical characteristics or abilities, which are evinced by students in an ascending order. These eight characteristics are arranged in ascending order of advancement and subdivided into three sequential levels: (A) analyzing the system components (e.g., identifying the components and processes of a system); (B) synthesizing system components (e.g., identifying dynamic relationships within the system, and organizing the system's components, processes, and interactions, within a framework of relationships); and (C) implementation (e.g., thinking temporally, identifying patterns and making generalizations). Each level of systems thinking in this model serves as the prerequisite and the basis for developing the thinking skills on the level above.

Summarizing, three generally agreed-upon central skills of systems thinking are proposed in the literature (e.g., Ben Zvi Assaraf and Orion, 2005; Mehren et al., 2018; Mambrey et al., 2020): (1) "identifying system organization": identifying a complex phenomenon in terms of its organization as a system and be able to describe the relevant components and patterns within it; (2) "analyzing system behavior": examining the system's development and functional processes, as well as both direct and indirect cause-and-effect relations between the identified elements of the system; and (3) "system modeling": modeling the hypothesized prospective target states of the system. This study explores these skills using the CMP conceptual framework. Specifically, Hmelo-Silver et al. (2017) declared that the CMP conceptual framework reflects the mechanistic reasoning of ecosystem learning, in the context of a complex system. Since the aim is to explore students' conceptualization of the underling mechanism of the COVID-19 outbreak, this framework is appropriate for this study allowing identify system thinking learning trajectories.

2.2. Concept maps as a tool for the externalization of mental system models

One of the key principles in planning the teaching of complex systems is representing the conceptual framework explicitly to the students and helping them to represent their mental models explicitly (Knippels and Waarlo, 2018; Eberbach et al., 2021). The external representation of mental models is a useful means of assessing students' understanding of the multilevel structure that characterizes complex, non-linearly organized biological phenomena (Dauer et al., 2013). One way to do this is to use concept maps as a visual means of externalizing and examining students' internal mental models (Kinchin et al., 2000; Hay et al., 2008; Brandstädter et al., 2012). Snapir et al. (2017) emphasize the importance of presenting complex systems within a conceptual framework that addresses, expresses and organizes all of the system's components and the relationships between them. Such conceptual representations can not only help students organize their ideas, but might also make it possible to identify differences in the extent of individuals' system thinking skills, and of the development of these capacities within each learner.

The importance of concept maps as a research tool lies in the possibility of conducting comparisons between multiple maps—either to compare the mental models of different people or to compare the mental models of the same person at different points in time. Comparisons between the maps of multiple students can also help researchers and educators identify and assess recurring patterns in the development of students' systems thinking (Dauer et al., 2013). Concept maps can also be analyzed for their structural attributes. The structural attributes reflect the way the concepts are organized and connected in the map, such as identifying junctions where more than two concepts are connected to another one (Tripto et al., 2017; Nesimyan-Agadi and Ben-Zvi Assaraf, 2021). This is important for complex phenomena in which students may display fragmented understanding (Kinchin et al., 2000). External representations of mental models (like concept maps) are used to evaluate not only conceptual understanding, but also the ability to solve problems in a complex system's content (Johnson-Laird, 2001, 2004).

Nevertheless, Kinchin (2011, 2014), claimed that "poor" maps are not always indicators of poor performance and "good" maps not always predictors of good performance. There is no one common determination whether a concept map is really good in terms of indicating the presence of a sophisticated understanding. For example, a spoke structure may develop into a chain or a network over a period of time as the student's understanding develops and is more systemized and complex in response to further learning.

Akçay (2017) used concepts maps to identify prospective elementary science teachers' difficulties regarding the connection between photosynthesis and cellular respiration processes in terms of energy and matter cycling. De Sousa et al. (2019) analyzed primary school teachers systems thinking concept maps on the interconnectedness of soil and climate change. The research study indicates that the teachers struggled to use systems thinking to illustrate understanding of the interconnectedness of soil and climate change, for example, how healthy soils can mitigate the impact of climate change. Ben Zvi Assaraf and Orion (2005, 2010) demonstrated how concept maps allow students at the junior high school level, to link processes to the nodes representing the system components to present causal dynamics and cyclic mechanism, within the earth system. Although concept maps enable relational links to be made between relevant concepts, Safayeni et al. (2005) pointed their limitation in to capture "cyclical" relationships representing complex natural and social systems. Therefore, they suggested cyclic concept maps for representing dynamic relations and hybrid maps for representing both the concept map and the cyclic concept map portion of a knowledge representation in an aggregated map.

2.3. Aims and research questions

This is a mixed methods study aiming at identifying PBTs' systems thinking in the context of COVID-19 using concept maps. To do so, concept maps were qualitatively analyzed for their complexity and structural attributes, and statistical analyses between obtained scores was performed.

The following research questions are addressed in this paper:

What are the complexity and structural attributes of PBTs' concept maps about COVID-19?

What are the relationships between the complexity and structural attributes of PBTs' concept maps about COVID-19?

3. Methodology

3.1. Context and participants

This study was carried out at one public university in Germany, that is, in the first phase of teacher education. Preservice teachers in Germany usually study two subjects in a six-semester bachelor's program, followed by a four-semester master's program (concurrent teacher education programs). At the end of their studies, preservice teachers are expected to develop basic professional knowledge and competences needed for their profession (Neumann et al., 2017). These include knowledge and competences regarding complex biological phenomena and systems thinking skills (Fanta et al., 2019).

The sample of this study consists of concept maps produced by PBTs from the fourth (i.e., the last) semester of the Master of Education program. All students enrolled in a course focusing on biology education research, were asked to participate in this study by producing a concept map on the COVID-19 pandemic. The participation in the study was not mandatory for the course; participation was voluntary and anonymous. Researchers and participants had no formal relationships to one another.

3.2. Tools and methods

3.2.1. Concept maps

Twenty seven concept maps were produced and submitted by students in the course after receiving explicit instructions provided both orally by the course teacher and as written text in the task introduction. All produced concept maps included text on most or all of the connecting arrows and were taken for analysis.

3.2.2. Semi-structured interviews

To test whether the aspects of complexity identified in students' concept maps reflect their systems thinking and understanding, semi-structured individual interviews with three additional PBTs were conducted, in which they were asked to reflect about their concept map as a visual representation of COVID-19 outbreak as complex phenomena, provide evidence for that given connection, and add concepts or connections if needed. The aim of the interviews was stimulating students' explicit use of the system characteristics to evaluate how the analysis capture their system thinking reasoning in terms of the components (C) of a particular phenomenon (P) and how they interact to result in a specific mechanism (M) of the phenomenon (COVID-19 outbreak).

Interview questions and protocol were based on Tripto et al. (2016) and revised collaboratively developed by all authors (interview questions provided in Supplementary material 3). The three interviewed students, named students A, B, and C, were females master students in the same program as the rest of the study participants and were selected as a convenience sample. Interviews lasted 20–30 min each. An example of one of the interviewed students' concept map is provided in Figure 1.

3.3. Data collection

The PBTs were asked to anonymously produce a concept map that describes their understanding of the COVID-19 outbreak ("In recent months, we have experienced COVID-19 as a global phenomenon. Please create a concept map that describes your understanding of the various factors influencing the spreading of COVID-19"). To produce and save the concept maps, the PBTs used SageModeler (Bielik et al., 2019), an open access online drawing tool, which allowed them to add as many boxes to the drawing board, to connect between them with arrows, and to label the boxes and arrows. The software allowed the PBTs to create and digitally send a shared link of their final concept map. PBTs were not provided with specific instructions on how to produce a concept map, as they were already familiar with this method from their previous studies. As far as we know, PBTs did not receive any explicit teaching materials concerning COVID-19 in their academic studies at the time of administration of the task. However, it was accepted that they all were exposed and informed of the COVID-19 situation from media and other sources.

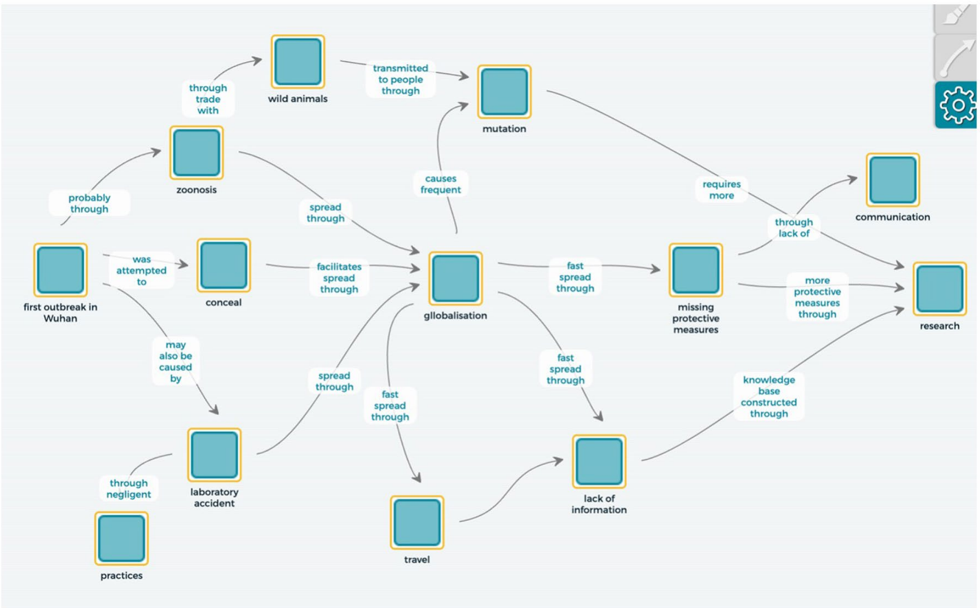

FIGURE 1
Concept map of interview student C.

The semi-structured interviews that were conducted with three additional PBTs took place online and were led in German by one of the authors. Each interview lasted between 20 and 30 min and all interviews were video recorded. Interviews were fully transcribed and translated into English. Authors collaboratively analyzed the interview transcripts.

3.4. Analysis

All 27 maps were translated from German to English and qualitatively analyzed for complexity and structure attributes. The analysis was conducted as a collaborative social interaction over time, with the combined efforts of three of this manuscript's authors, which are researchers in the field of science education. The concept maps were examined repeatedly, with the CMP model serving to guide the reading and the analysis toward the formation of a series of codes. Since every researcher interprets data according to their own subjective perspective, content validation was done until 90% agreement was achieved. Following this, interrater agreement was tested by two researchers independently and Cohen's Kappa ($K = 0.85$) indicates an "almost perfect" (Landis and Koch, 1977) interrater agreement. Cases of disagreement were resolved by discussion until full agreement was reached.

Because of the multidisciplinary nature of the COVID-19 outbreak, almost all concept maps described systems that included both biological concepts (e.g., COVID-19 outbreak, virus mutation, infectious rate, etc.) and social concepts (e.g., lockdown, globalization, travel restrictions, etc.), with the exception of student #17 map which included only biological concepts.

To test students' understanding of social and biological concepts, student in the interview were asked to identify these concepts in their maps. All three students were able to correctly identify and distinguish between social and biological concepts. For example, one student said:

"*The social aspect for me would be, on the one hand, the interaction of organisms in factory farming or also the volume of travel or the density of people in cities, that would be the social aspect for me. How do people deal with each other, as well as lack of information and governments. So social constructs in society. And the biological* [concepts] *would be for me then just something like mutations, infection times, but also intervention in nature and habitats, where it is for me then really about the natural factor.*" (Student B interview).

The analysis did not focus on the disciplinary content since this was not the aim of this study, as it aims to characterize the system language in the maps rather than assessing the sophistication level of students' biological conceptual knowledge.

Based on the statistical analysis that was performed to address the second research question, two exemplary concept maps were chosen for in-depth analysis. The two concept maps represent typical cases that demonstrate the statistical correlations that were found.

3.4.1. Complexity attributes

For complexity attributes, maps were analyzed based on Hmelo-Silver et al. (2017) CMP framework, which provides a representation of all the system's attributes. The analysis was performed by Snapir et al. (2017) for specific CMP and structural attributes was carried out, as described below.

3.4.4.1. Components

Concept maps were analyzed for component attributes that describe COVID-19 as complex systems. As suggested by Ben Zvi Assaraf et al. (2013), biological concepts in each map were analyzed for their organizational level, with three types of biological organizational levels that were classified: only macro level concepts, macro and cellular micro level concepts, and macro level and

TABLE 1 Biological organizational levels analyzed in concept maps in this study.

Level	Description	Example of concepts
1	Maps that include only macro level concepts	Habitats, population, animals, humans
2	Maps that include both macro level and micro cellular level concepts without any micro molecular level concepts	Virus, immune system cells
3	Maps that include at least one micro molecular level concept	mRNA, mutation

TABLE 2 Type of relationships in concept maps.

#	Type	Description	Possible connecting terms	Example of constructs
1	Simple structural relationships	Relationships describing how components are connected or part of other components	"Part of," "connects to," "has"	"Disease has severe symptoms," student #5
2	Simple mechanistic relationships	Relationships describing how components are affecting other components without determining the kind of effect or rate	"Influence," "lead to," "effects"	"COVID-19 influences economy of countries," student #8
3	Sophisticated time-based relationships	Relationships describing the rate and trend of the effect	"Increase," "decrease"	"Mutation can increase COVID-19 outbreak," student #14

molecular micro level concepts (elaboration and examples provided in Table 1). These organizational levels represent the commonly used levels when examining biological phenomena. In their interviews, all three students were able to identify the correct biological organizational level of their biological concepts or to recognize which organizational levels are missing from their concept maps. For example, student C said: "*So the organism level I would definitely be the wild animals and the zoonosis, the molecular then would be the mutations.*"

3.4.1.2. Mechanism

To analyze the concept maps for mechanism attributes, specific processes and interactions between components and the outcomes of these interactions, such as feedback loops, were identified by analyzing the connections between concepts in the maps. Analysis included two categories: type of relationship and organizational level changes.

Type of relationship were coded based on the nature of connections between concepts in maps. Three types were identified, based on Tripto et al. (2017): simple structural relationships, simple mechanistic relationships, and sophisticated time-based relationships (see Table 2 for elaborated description and examples). Percentage of each type of relationships from total number of connections in each map was calculated. In their interviews, all students were asked to identify sophisticated time-based relationships in their maps and were able to correctly do so. For example, student B said: "*High travel increases the density of people in the cities, so to speak. And high travel volume also increases rapid spread. That would be something like that* [sophisticated time-based relationship]."

Organizational level change was defined as a connection between two concepts that are from different biological micro/macro hierarchical levels (e.g., viral RNA attacks human host, student #24). Percentage of organizational level changes was calculated as number of connections with organizational level change out of the total number of connections in the map.

In their interviews, students were able to identify organizational level changes. For example, student B said:

"*Then cellular to organism* [organizational level] *for me would be human infection and mutation. So, what happens at the cellular level and what effects it has on the organism. And then of course cellular to pandemic* [organizational level] *would be then from infection to rapid spread and then to pandemic.*" (Student B interview).

3.4.1.3. Phenomena

For the phenomena attributes, characteristics of the overall behavior or properties of the system that results from certain mechanisms or processes were analyzed. The phenomena present the macro scale of processes and patterns within a system (Tripto et al., 2017). Two categories were coded: number of mechanistic relationships chains and global dynamic concepts included in the maps.

A mechanistic relationships chain was identified as a sequence of three or more concepts connected by simple or sophisticated mechanistic relationships. For example, map of student #9 included the following chain: governments fight COVID-19 influences economy of countries. Total number of mechanistic relationships chains in each map was calculated.

To test this in the interviews, students were asked to identify mechanistic relationship chains in their maps. They were all able to correctly point out the chains in their maps. For example, student A said:

"*Yes, I think above all below left* [pointing at a series of variables in map]*: COVID, bat, patient zero, Wuhan, epidemic, globalization and pandemic, and maybe also individual countries. This is in any case a very long chain of events, at least that's how I thought of it and that's how I also started when constructing to show the temporal course* [of events]." (Student A interview).

Maps were also analyzed for including at least one global dynamic concept, such as immigration, trading between countries, moving of COVID-19 variants etc.

In their interviews, all students were able to identify these types of concepts, as student C said:

"*I have also written globalization here in the middle* [pointing at the concept on map] … *More contact with people, which comes about because of globalization, leads to more mutations, which is why more research must take place worldwide, which means also globally, because* *you have to gather the world's knowledge or global knowledge about this virus in order to draw conclusions from it*." (Student C interview).

3.4.2. Structural attributes

For the structural attributes, indicators were identified, which emphasize the structural aspects of the concept map as a lens for understanding students' mental model complexity. As analyzed by Snapir et al. (2017), structural indicators included the number of concepts, number of connections, and ratio between connections and concepts in each map. The higher the ratio between concepts and connections, the more structurally complex the map, since there are more concepts that are connected to each other. In addition, number of junctions was calculated. Junction was defined as a concept in the map that had more than two arrows going in or out of it. The more junctions, the more structurally complex the map.

The analysis process of the concept maps included the following steps: first, each concept was identified as biological or social. Each biological concept was coded as global or non-global. Each biological concept was than coded for its biological organizational level (macro, micro-cellular, or micro-molecular, see Table 1). Next, each connection between concepts was given a number and coded for type of connection, and whether it represents an organizational level change. Each map was than coded for the number of mechanistic connection chains, and all structural indicators were calculated.

To address research question two (i.e., relationships between the complexity and structural attributes), the data were *z*-standardized and the Spearman correlation coefficient was calculated. As there are 45 separate correlational analyses (Table 3), $p = 0.001$ (i.e., $p = 0.05/45$) was set as the criterion for significance to control the familywise error rate ("Bonferroni correction"; Field, 2013).

4. Results

4.1. Complexity and structural attributes of preservice biology teachers' concept maps

To address the first research question, what are the complexity and structural attributes of PBTs' concept maps about COVID-19, all 27 concept maps were analyzed and scored for complexity and structural attributes. Table 4 provides the descriptive statistics for complexity attributes. Full data obtained from all 27 maps is provided in Supplementary material 4. From the component perspective, in the organizational level attribute, about half of the maps included only macro level biological concepts (13 out of the 27 maps), while only 7 maps included also micro level concepts and 7 maps included also included molecular level concepts. From the mechanisms perspective, about 20% of the connections in the maps demonstrated organizational level changes, and most of the relationships in the maps were of the simple mechanistic type. From the phenomena perspective, maps included an average of about 5 mechanistic relationships chains.

Table 5 provides the descriptive statistics for the structural attributes. Maps included a wide range of number of concepts, connections and ratio between them, and an average of about 4.5 junctions in each map.

4.2. Relationships between complexity and structural attributes

To address the second research question, what are the relationships between PBTs' complexity and structural attributes as portrayed in their COVID-19 concept maps, correlational statistical analysis was performed (Table 3)—with a corrected criterion for significance of $p = 0.001$ as described above.

Concerning the relationship between complexity and structure indicators, the number of concepts was significantly positively correlated with the percentage of simple structural relationships ($r = 0.63$; $p < 0.001$). This means that the more concepts a concept map included, the higher was the amount of simple structural relationships in the map—and vice versa—but not the amount of more sophisticated relationships (i.e., simple mechanistic and sophisticated time-based relationships).

The number of mechanistic relationships chains was significantly positively correlated with all three other structural attributes besides concepts (connections: $r = 0.64$; $p < 0.001$; ratio between connections/concept: $r = 0.69$; $p < 0.001$; junctions: $r = 0.76$; $p < 0.001$). Hence, there is a positive association between these three structural attributes and the amount of mechanistic relationships chains in the concept maps.

4.3. Examples of concept maps

Two concept maps were chosen to further examine the correlations that were found between the structural and complexity attributes. Descriptive analysis of the maps is provided below.

The map produced by student #8 (Figure 2), demonstrates relatively low scores of structural and complexity attributes. From the structural perspective, the concept of COVID-19 is placed in the center of the map and most other concepts are connected to it. The map includes below average number of concepts and connections and below average ratio between connections and concepts (11 concepts, 10 connections, ratio of 0.91), and two junctions ("COVID-19" and "governments").

From complexity perspective, the component attribute includes only macro level components (e.g., "governments," "WHO," "Superspreader"). In the mechanism attributes, most of the connections (90%) are of the simple mechanistic type (e.g., "COVID-19 influences economy of countries") with no connection of the sophisticated time-based type, and with a relatively average percentage of the connections demonstrating organizational level change (20%, e.g., "patient zero unconscious spreading worldwide"). From the phenomena attributes perspective, this map has only four chains of mechanistic connections and it includes several global level concepts, such as "spreading worldwide" and "interconnected world globalization."

The map produced by student #24 (Figure 3), demonstrates relatively high structural and complexity attributes. From the structural perspective, this map demonstrated high level of interconnectedness among concepts. The map includes above average number of connections and very high ratio between connections and concepts (14 concepts, 23 connections, ratio of 1.64), and seven junctions (e.g., "outbreak of COVID-19," "risk of infection," "viral RNA" etc.). From complexity perspective, this map describes connections between both biological and social concepts, e.g., "risk of

TABLE 3 Results of correlational analysis (Pearson *r*) between all attributes (*z* standardized) considered in this study.

		2	3	4	5	6	7	8	9	10	11
1. Macro–micro level	*r*	−0.10	0.07	0.01	0.46	0.19	−0.19	0.14	0.02	−0.16	−0.13
	p	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
2. Simple structural relationships	*r*		−0.39	−0.45	−0.05	0.13	0.01	**0.63**	0.57	0.17	0.25
	p		n.s.	n.s.	n.s.	n.s.	n.s.	**<0.001**	n.s.	n.s.	n.s.
3. Simple mechanistic relationship	*r*			**−0.65**	0.30	0.13	0.01	−0.23	−0.18	0.00	−0.02
	p			**<0.001**	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
4. Sophisticated time-based relationship	*r*				−0.25	−0.24	−0.01	−0.30	−0.30	−0.14	−0.19
	p				n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
5. Organizational level change	*r*					−0.02	−0.29	−0.15	−0.09	−0.02	−0.12
	p					n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
6. Mechanistic relationships chain (#)	*r*						0.16	0.41	**0.64**	**0.69**	**0.76**
	p						n.s.	n.s.	**<0.001**	**<0.001**	**<0.001**
7. Global dynamic concepts (yes/no)	*r*							0.20	0.21	0.10	0.23
	p							n.s.	n.s.	n.s.	n.s.
8. Concepts	*r*								**0.85**	0.17	0.41
	p								**<0.001**	n.s.	n.s.
9. Connections	*r*									**0.65**	**0.77**
	p									**<0.001**	**<0.001**
10. Connections/concepts	*r*										**0.87**
	p										**<0.001**
11. Junctions											

Highlighted in gray: correlations between complexity and structure indicators. Statistically significant correlations are highlighted in bold ($p < 0.001$); $N = 27$.

TABLE 4 Descriptive statistics for complexity attributes.

	Range	Mean	*SD*
Components			
Organizational level[1]	1–3	1.78	0.85
Mechanisms			
Simple structural relationships (% of relationships in maps)	0–77.27	27.50	22.10
Simple mechanistic relationships (% of relationships in maps)	0–100	53.24	25.94
sophisticated time-based relationships (% of relationships in maps)	0–100	19.26	26.76
Organizational level change (% of maps)	0–57.14	19.26	18.74
Phenomena			
Mechanistic relationships chains (#)	0–10	4.56	2.46
Global dynamic concepts (no/yes)	0 or 1	0.67	0.48

[1]Organizational levels includes 1 (only macro level concepts), 2 (macro and micro cellular level concepts), and 3 (including micro molecular level concepts).

infection" connects with the social concept "protective measures" and the biological concepts of "viral RNA" and "number of infections." The component attributes include macro level components (e.g., "aerosol"), and one micro molecular level component, "viral RNA." In the mechanism attributes, the map includes connection of all types, with 43.5% of them of the structure type (e.g., "mouth-nose covering is protective measures"), 30.4% of them are of simple mechanistic type (e.g., "risk of infection affects number of infections"), and 26.1% of them are of the sophisticated time-based type (e.g., "aerosols decreased by mouth-nose covering"). From the phenomena attributes perspective, this map has eight chains of mechanistic connections, however it does not include any global level concepts.

5. Discussion

This study explores PBTs' concept maps that externalize their mental models of one of the most pertinent examples of a complex,

TABLE 5 Descriptive statistics for structural attributes.

	Range	Mean	*SD*
Concepts (#)	8–30	14.37	4.84
Connections (#)	8–33	16.70	6.74
Ratio connections/concepts	0.89–1.81	1.15	0.24
Junctions (#)	0–14	4.56	3.07

socio-scientific system—the COVID-19 pandemic. The maps created by the students expressed the CMP complexity attributes, encouraging learners to explore the parts or components of the system (C) and to generate or recall plausible mechanisms (M) that result in the emergence of the observed phenomenon (P) (Hmelo-Silver et al., 2017). The concept maps as a conceptual cognitive modeling tool was used to help students construct explanatory models in terms of CMP, allowing students to create, note, and link representations with the nodes representing the system components and links representing mechanisms.

The first research question focused on what are the complexity and structural attributes of PBTs' concept maps about COVID-19. Using the CMP framework, It was found that most maps did not fully address the mechanistic chain of events describing how the COVID-19 outbreak spread out, as evident from the relatively low number of sophisticated time-based relationships and the low number of mechanistic relationships chains. Also, it was found only few incidents of cross-level reasoning, as evident from the low percentage of maps with organizational level change in the relationships. These findings indicate that PBTs did not have a sophisticated perception of COVID-19 as a complex phenomenon at the time of the activity. This could be explained by the fact that the concept maps were collected in the first months of the COVID-19 outbreak, when not enough information was known about the pandemic and the disease. Another possible explanation is that the task itself did not provide appropriate guidance or supports for the students to produce a sophisticated concept map of the phenomenon.

The second research question focused on what are the relationships between the complexity and structural attributes of teachers' concept maps about COVID-19. The results suggest that the appearance of many concepts does not necessarily indicate high level of complexity, as indicated by the positive correlation between the percentage of simple structural relationships (complexity attribute) to the number of concepts in the map (structural attribute). On the other hand, the results indicate that higher structural sophistication (i.e., high number of connections and junctions, and higher ratio between connections and concepts) could be associated with the complexity level of the map, as evident by the positive correlation between these structural attributes to the number of mechanistic relationships chains (complexity attribute). These findings support the assumption that concept maps are external representation of learners' mental models and that the organizational structure of the map reflects the way learners reorganize the concepts in their mental models (Kinchin et al., 2000; Hay et al., 2008). Understanding how students' systems thinking advances is essential in order to develop and facilitate a pedagogical scaffolding that allows students to engage in counterintuitive modes of thought and overcome the variety of cognitive barriers that can prevent them from fully understanding the system's complexity (Snapir et al., 2017).

This study emphasizes the potential of concept maps as a tool to identify understanding of complex systems. Concept maps are a powerful instrument for knowledge integration *and* externalization, helping students advance to higher levels of systems thinking, while also allowing researchers access to their externalized mental system models (Nesbit and Adesope, 2006; Dauer et al., 2013; Schwendimann and Linn, 2016; Hmelo-Silver et al., 2017).

5.1. Cross-level reasoning

A pertinent outcome of this study was that the students' concept maps showed very little evidence of cross-level reasoning. Biological phenomena manifest themselves at various levels of organization (Gilissen et al., 2021). As noted by Verhoeff et al. (2008), in order to understand biological phenomena, students need to connect concepts and processes across a single level of organization (horizontal coherence) and concepts and processes on different levels (vertical coherence). By asking the students to portray COVID-19 as a complex system, the PBTs were expected to represent different levels of biological organizational levels and acknowledge the various interconnections between them. It is possible that the students' emphasis on the social aspects of the pandemic limited this element in their concept maps by creating an over-representation of macro level system components. Indeed, fewer than one third of the maps included cellular level concepts (e.g., virus) or molecular level concepts (e.g., mRNA) that are essential for cross-level reasoning.

Cross-level reasoning is challenging to both preservice and in-service teachers (Gilissen et al., 2020). In this regard, various researchers have adopted the "yo-yo" learning and teaching strategy to assist teachers to explicitly engage in cross-level reasoning (see, for instance Knippels et al., 2005; Verhoeff et al., 2008; Jördens et al., 2016; Knippels and Waarlo, 2018). Moving up and down the levels of organization is the underlying principle of yo-yo learning, and this technique has been valuable for structuring learning sequences and guiding teaching processes. This emphasizes the role of explicit guidance in developing systems thinking. As Mor and Zion (2019) noted, without explicit teaching that emphasizes the connection between micro and macro levels in the system's hierarchy, students have difficulty seeing the interactions that make complex system patterns like homeostasis possible.

In this study, the task did not explicitly prompted students to use cross-level reasoning in their concept maps. One strategy that could be implemented in future tasks is to prompt students to use explicit mechanisms that involve cross-level reasoning in their explanations. This was recently presented by Gilissen et al. (2021), who asked secondary school students to formulate a hypothesis to explain why Tibetan people are naturally more capable than Dutch people of climbing Mount Everest. The aim was to prompt students to reason between the different levels of biological organization (Mount Everest on the ecosystem level, Tibetan people on the population, respiratory system on organism levels, and genes on the cellular level).

Furthermore, from methodological perspective, although concept maps were already proven to be fruitful in the context of systems thinking and they are known for their capability to foster conceptual system interrelations, It is suggested that presenting cross-level reasoning using concept maps may be challenging for PBTs. It is therefore suggested that future research should combine zooming with concept-mapping (Schneeweiß and Gropengießer, 2022). In this approach, vertical arrows indicate vertical

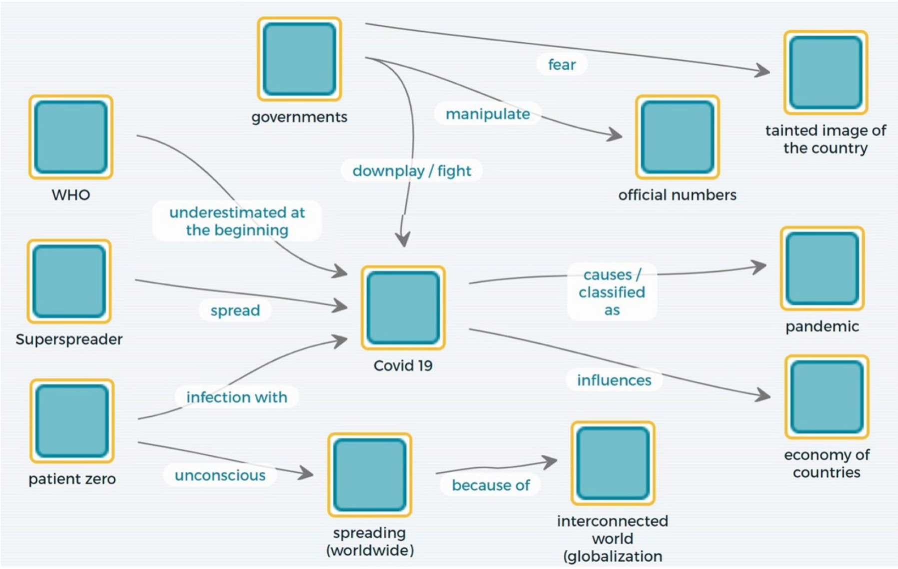

FIGURE 2
Concept map of student #8.

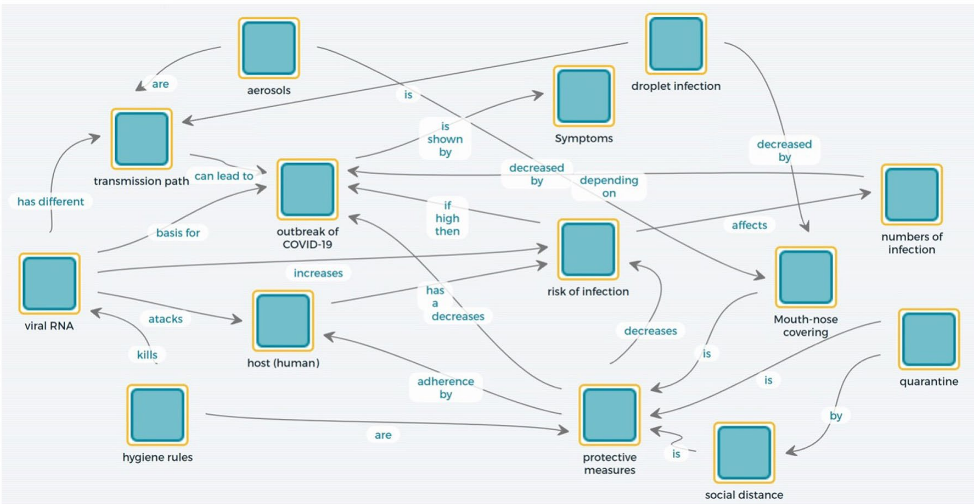

FIGURE 3
Concept map of student #24.

interrelation; horizontal arrows indicate horizontal interrelation, enabling the student present a sophisticated model of cross-level reasoning. The zoom map fosters students' causal explanations across levels of organization through the inherent demand to consider the respective levels. Therefore, the zoom map may help students structure and interrelate fragmented knowledge and achieve integrated knowledge.

5.2. Mechanistic reasoning

Understanding biological phenomena entails an understanding of the causal relationships across different levels of organization that result in the emergent phenomenon (Knippels and Waarlo, 2018; Asshoff et al., 2020). According to Krist et al. (2019), thinking across levels is an essential heuristic in mechanistic reasoning, which allows students to explain and make predictions about phenomena, directs their intellectual work and implicitly guides mechanistic reasoning. In this study most of the students expressed simple mechanistic relationships, describing how components are affecting other components without determining the kind of effect or its rate. In dynamic systems, two events may be connected, but separated from one another in space and time. Thus, recognizing dynamism also means identifying the interaction between events and predicting the consequences of changes (Hmelo-Silver et al., 2000). In this study, only some of the maps presented sophisticated time-based relationships, describing the rate and trend of the effect. This was reflected in the structure of the concept maps: Very few of which presented a chain of mechanistic relationships, identified as a sequence of three or more concepts connected by simple or sophisticated mechanistic relationships.

Hmelo-Silver et al. (2000) argued that when engaging with complex systems, novices tend to focus on readily observable and stable structures, rather than acknowledging invisible elements, dynamic processes, and exhibit mechanisms and outcomes as experts do. Studies have shown that difficulties with complex systems extend beyond secondary school students to preservice teachers and practicing teachers as well (Yoon et al., 2017, 2018). Akçay (2017), for example, examined advanced education students who intended to pursue science teaching. He found that they had difficulties with micro–macro relations and cross-level reasoning, and with understanding energy flow and matter cycles. Similarly, Haskel-Ittah et al. (2020) have explored undergraduate students' mechanistic reasoning regarding phenotypic plasticity, where genes and environment interact to produce different phenotypes. When trying to explain the mechanisms involved in complex phenomena, first-year students tend to refer to the direct effect of the environment, while third-year students refer more to sensing-responding mechanisms that involve indirect relationships. A possible explanation for this is that students may need more domain-specific knowledge in order to be able to utilize more sophisticated mechanistic reasoning. Since this study did not include a content related intervention about COVID-19 as complex systems, additional studies are required that focus on students' ability to perceive the biological mechanism related to COVID-19 outbreak.

5.3. Social and biological aspects of COVID-19

Almost all of the students' concept maps included both social and biological concepts. This result highlights the multidisciplinary nature of the COVID-19 pandemic, and its profound effect on all aspects of society, including psychological, social, and neuroscientific effects (Holmes et al., 2020). The multidisciplinary nature of complex systems like the COVID-19 pandemic requires educators to expand and adapt models of complexity beyond the biological. Mehren et al. (2018) have developed a competence model for systems thinking in the context of socio-ecological systems. Their competence model consists of four dimensions, namely system organization, system behavior, system-adequate intention to act, and system-adequate action. Reiss (2020) pointed to the potential opportunities for promoting cross-curricula and interdisciplinary approaches in school STEM lessons when addressing wider societal issues like COVID-19. However, engaging with complex socio-scientific issues, such as COVID-19, requires specific knowledge and skills, such as the understanding and competence to comprehend and follow arguments embedded in a complex social and political context. Furthermore, these must be combined with scientific content knowledge, knowledge about the nature of science, and higher-order thinking (Sadler, 2009). Uskola and Puig (2023) employed concept maps as a research tool to analyze dimensions related to systems thinking (System structure) and futures thinking developed by a group of pre-service elementary teachers. They demonstrated how different activities designed were effective in relation to scientific reasoning about the origin of pandemics and possible ways to prevent them as socioscientific problems.

5.4. Limitations, recommendations, and conclusions

This study has several limitations. First, this study included only a small sample of concept maps that may not represent the broader population of PBTs. In addition, the concept maps were produced in the first few months following the COVID-19 outbreak, when not enough understanding of the phenomena was established. Also, the task was performed remotely (because of the COVID-19 restrictions), which may have influenced students' engagement in the task. It is suggested that future studies will include an intervention that explicitly prompts students to use system language and guidance about COVID-19 as complex phenomenon. Another follow-up study can compare these results to PBTs' concept maps about COVID-19 several years after the outbreak of the pandemic, when much more is known and understood about the pandemic outbreak. This may reveal possible increase in sophistication of PBTs' understanding of COVID-19 as a complex phenomenon as the knowledge about it developed.

From a pedagogical perspective, these findings suggests that in order to support teachers' and students' level of systems thinking, they should be explicitly directed to increase the complexity of their concept maps by enhancing the plethora of network connections between the concepts in their maps. This can be achieved by directing them to consider adding a range of sophisticated causal relationships chains to demonstrate the complexity of their understanding of the target phenomenon. In addition, teachers can support their students' systems thinking by reflecting on their produced concept maps and directing their attention to include biological and social aspects, address different organizational levels, and provide sophisticated mechanistic relationship rather than simple structural connections.

Altogether, this study provides a detailed analysis of PBTs' understanding of COVID-19 as a complex phenomenon, adding to the research fields' understanding of the relationships between complexity and structural attributes of concept maps as representations of students' mental models. These findings further support the argument that the number of concepts in produced maps does not necessarily reflect students' systems thinking or the sophistication level of their mental models. However, higher number of connections and junctions in concept maps can indicate a higher sophistication level of students' mental models. These findings contribute to the understanding of systems thinking and complexity, as reflected in students' mental model concept maps, by pointing out to the possible connection between higher structural sophistication of maps to its complexity level. These findings contribute to the understanding of students' and teachers' systems thinking as well as to possible scaffolds and practices that can be used to further support their systems thinking skills. Youth need an opportunity to engage with the science and practice of infectious disease epidemiology in classroom environments. Kafai et al. (2022) scoping review of interventions in K-12 education showed, that learning and teaching about infectious diseases in science education is not yet embrace the full spectrum of practices that provide K-12 students to collaboratively investigate growing levels of complexity around infectious disease as a complex system that included variability and randomness.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

TB, JJ, and OB contributed to the conception and design of the study. JJ and DK performed the data collection. TB, MK, and JJ organized the database. JJ and MK performed the statistical analysis. TB and OB wrote the first draft of the manuscript. TB, MK, and OB wrote sections of the manuscript. All authors contributed to manuscript revision, read and approved the submitted version.

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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.

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Supplementary material

The Supplementary material for this article can be found online at:https://www.frontiersin.org/articles/10.3389/feduc.2023.1107000/full#supplementary-material

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EDITED BY
Moritz Krell,
University of Kiel, Germany

REVIEWED BY
Rieke Ammoneit,
University of Kiel, Germany
Dirk Krüger,
Freie Universität Berlin, Germany
MaryKay Orgill,
University of Nevada, Las Vegas, United States

*CORRESPONDENCE
Emil Eidin
✉ eidinema@msu.edu

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The effect of using different computational system modeling approaches on applying systems thinking

Emil Eidin[1,2]*, Jonathan Bowers[1], Dan Damelin[3] and Joe Krajcik[1]

[1]CREATE for STEM Institute, Michigan State University, East Lansing, MI, United States, [2]College of Education, University of Wyoming, Laramie, WY, United States, [3]The Concord Consortium, Concord, MA, United States

This paper discusses the potential of two computational modeling approaches in moving students from simple linear causal reasoning to applying more complex aspects of systems thinking (ST) in explanations of scientific phenomena. While linear causal reasoning can help students understand some natural phenomena, it may not be sufficient for understanding more complex issues such as global warming and pandemics, which involve feedback, cyclic patterns, and equilibrium. In contrast, ST has shown promise as an approach for making sense of complex problems. To facilitate ST, computational modeling tools have been developed, but it is not clear to what extent different approaches promote specific aspects of ST and whether scaffolding such thinking should start with supporting students first in linear causal reasoning before moving to more complex causal dimensions. This study compares two computational modeling approaches, static equilibrium and system dynamics modeling, and their potential to engage students in applying ST aspects in their explanations of the evaporative cooling phenomenon. To make such a comparison we analyzed 10th grade chemistry students' explanations of the phenomenon as they constructed and used both modeling approaches. The findings suggest that using a system dynamics approach prompts more complex reasoning aligning with ST aspects. However, some students remain resistant to the application of ST and continue to favor linear causal explanations with both modeling approaches. This study provides evidence for the potential of using system dynamics models in applying ST. In addition, the results raise questions about whether linear causal reasoning may serve as a scaffold for engaging students in more sophisticated types of reasoning.

KEYWORDS

systems thinking, computational system modeling, system dynamics, linear causal reasoning, static equilibrium models

1. Introduction

Systems thinking (ST) has gained recognition as a necessary approach for addressing complex problems in various domains (Assaraf and Orion, 2005; Jacobson and Wilensky, 2006; Meadows, 2008). Although much of the research in ST was in disciplines such as biology and Earth science (Yoon et al., 2018), lately there has been a growing awareness and advancement in integrating ST in chemistry education (Flynn et al., 2019; Orgill et al., 2019; York et al., 2019), moving the field forward in an effort to apply ST across disciplines. In recent years, the integration of ST into science education standards has been adopted by a number of countries (National Research Council, 2012; Reynolds et al., 2018; Chiu et al., 2019). According to Meadows (2008), a system is an interconnected set of elements that demonstrates behavior that cannot be understood by examining individual elements in isolation. There have been numerous efforts to operationalize ST and develop frameworks for evaluating its application (Richmond, 1993; Assaraf and Orion, 2005; Hmelo-Silver et al., 2007b).

Despite various approaches in developing students' understanding of ST, educators continue to face challenges in its application. Many students explain complex phenomena using simple linear cause and effect relationships (Sweeney and Sterman, 2000; Chi, 2005; Chi et al., 2012; Grotzer et al., 2013; Tripto et al., 2013). However, simple linear cause and effect mechanisms cannot account for phenomena that involve equilibrium, feedback, cyclic patterns, and perturbations (Richmond, 1993). Hence, there is a need to facilitate student understanding of non-linear system behaviors to cultivate scientific reasoning and produce scientifically literate citizens (Meadows, 2008; Ke et al., 2021). Despite attempts to engage students in mechanisms that go beyond linear causal thinking, students have shown resistance to adopting an ST approach (Assaraf and Orion, 2005; Chi, 2005; Hmelo-Silver et al., 2007a; Chi et al., 2012).

It has been nearly four decades since scholars began attempting to utilize technology to enhance students' understanding of ST (Costanza, 1987; Mandinach, 1989; Metcalf et al., 2000). Computational modeling tools have emerged as a promising avenue. There are three main approaches in the field: static equilibrium modeling, system dynamics modeling, and agent-based modeling. Static equilibrium modeling is a computational approach that facilitates the creation of linear and/or branching cause and effect relationships such that changes to one variable are instantly reflected by changes in the values of related linked variables (Bielik et al., 2018). Unlike static equilibrium modeling, system dynamics modeling allows representation of changes in a system over time (Sterman, 2002; Martinez-Moyano and Richardson, 2013), opening the door for representing dynamic equilibrium and feedback. Agent-based modeling, another time-based modeling system, enables users to explore the actions of individual agents in the system and observe the impact of their interactions on the emergent behavior of the system (Wilensky and Resnick, 1999; Jacobson and Wilensky, 2006). All of the approaches enable users to test and evaluate their models (Bielik et al., 2018). In this paper, we focus on static equilibrium and system dynamics modeling. There are two main reasons to prioritize these two approaches. Firstly, both approaches share similar underlying affordances that enable the setting of causal relationships between variables. Secondly, from a practical standpoint, there is a software tool that we will discuss in detail later, which facilitates seamless switching between these approaches. This feature significantly reduces the learning curve associated with adapting to a new digital environment.

Few studies have compared the effects of various modeling approaches on students' application of ST (Carolyn and Lee, 2019). In this study, we advance our understanding of how to support students in system modeling by analyzing the effects of static equilibrium and system dynamics modeling on students' explanations and the mechanisms they use to understand complex phenomena. We also explore to what extent engagement in a simpler modeling approach serves as a scaffold to support students in applying more complex aspects of ST. Our goal is to gain insights into computational tools and scaffolds that can expand students' ideas from linear to more complex non-linear thinking.

2. Theoretical framework

2.1. Linear causal reasoning

Linear causal reasoning is a fundamental way in which individuals explain the world and make sense of their surroundings from a young age (Driver et al., 1985; Leslie and Keeble, 1987). This method of explanation is commonly used in science to describe mechanisms, such as the direct linear relationships between mass, acceleration, and force in Newton's third law. Science education often teaches students to reduce complex mechanisms to simple cause and effect relationships, leading to a reductionist approach across disciplines. This has been observed in various areas of study, such as Earth science (Raia, 2005), biology (Gilissen et al., 2019), and chemistry (Tümay, 2016). Additionally, linear causal reasoning often leads to assigning a central agent in a domino-like mechanism (Resnick, 1996; Galea et al., 2010; Kahneman, 2011). While appropriate for understanding topics such as Newton's third law, this method of explanation is particularly problematic for phenomena with dynamic features such as erosion, evolution, disease spread, and global average temperature rise (Sander et al., 2006).

In this paper, we use the term "linear causal reasoning" as coined by Driver et al. (1985) to refer to thinking about sequential chains of causes and effects. This tendency has further generated more nuanced terminologies. Chi et al. (2012) made a distinction between a direct-causal schema and an emergent-causal schema. Accordingly, the direct causal schema relies on linear, narrative-like cause and effect scripts that when applied in the context of complex and non-sequential processes often result in developing non-canonical understandings. Perkins and Grotzer (2005) suggested evaluating students' explanations according to dimensions of causality, differentiating between various levels of causal explanations in each of these dimensions. Grotzer et al. (2013) differentiated students' explanations as event-based or process-based. For example, they noticed that students interpret ecosystems as distinct events with linear cause and effect explanations (event based), instead of a dynamic time-based mechanism (process based), which is more appropriate in that context.

2.2. Systems thinking

Although students need to develop linear causal reasoning, having access to only this type of reasoning restricts the types of problems and phenomena students can explore. Enabling students to familiarize with non-linear reasoning prepares them to be scientifically literate citizens equipped with the intellectual tools to understand and address complex issues and phenomena such as global warming, the spread of diseases, and the impact of invasive species on ecosystems (Liu and Hmelo-Silver, 2009; Yore, 2012).

To support students in developing a more comprehensive understanding of the world, scholars examined the reasoning processes used by experts when facing complex problems (Hmelo-Silver et al., 2007b). This line of inquiry has led to the recognition of a

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broad range of reasoning skills commonly referred to as ST (Senge and Sterman, 1992; Richmond, 1993; Sterman, 2002; Assaraf and Orion, 2005; Meadows, 2008). Despite the variations in ST approaches, there is a general agreement about the key aspects that support students in solving complex problems and understanding complex phenomena (Sweeney and Sterman, 2000; Hmelo-Silver et al., 2007b; Assaraf et al., 2013). A recent literature review (Shin et al., 2022) summarized ST aspects that are commonly found across various studies on the topic, including *framing problems or phenomena in terms of behavior over time* (Richmond, 1993; Forrester, 1994), *engaging in causal reasoning* (Stave and Hopper, 2007; Meadows, 2008), and *identifying interconnections and feedback* (Richmond, 1993; Sweeney and Sterman, 2000; Haraldsson, 2004; Zuckerman and Resnick, 2005).

Perkins and Grotzer (2005) devised a framework that identifies dimensions of causality and characterizes each dimension's complexity level. This framework can be used to evaluate the application of systems thinking in student explanations of phenomena. The dimensions are *agency*, *interactive patterns*, *mechanism*, and *probability*.

- *Agency* refers to the attribution of the cause given for a phenomenon. The complexity of this causal dimension can range from centralized agents with intentional cause to decentralized agents with non-intentional cause such as self-organizing or emergent systems.
- *Interactive patterns* describe the complexity of the causal relationship between components in the system. Interactive patterns range from sequential patterns (e.g., A causes B) to simultaneous patterns (e.g., patterns that include feedback and cycles).
- *Mechanism* refers to the scale or level used to explain a phenomenon. Mechanisms range from an explanation that includes macroscopic entities to an explanation that includes microscopic entities and underlying laws.
- *Probability* denotes explanations that range from deterministic to random behavior of the components in the system.

Utilizing the more complex levels within each causal dimension is essential to make sense of complex phenomena that are often characterized by steady states, feedback, cyclic patterns, dynamic relationships, and occasional perturbations (Meadows, 2008). In addition, ST has recently been recognized in K-12 science curriculum guides (National Research Council, 2012). The challenge researchers have experienced is devising strategies to support students in applying ST. One of the most promising avenues is in the use of computational models (Sterman, 2002; Gilissen et al., 2019).

2.3. Computational systems modeling

Computational systems modeling offers a valuable tool for students to develop their problem-solving skills and explain complex scientific phenomena (Stratford et al., 1998; Sins et al., 2009; Chandrasekharan and Nersessian, 2015; Shin et al., 2022). Particularly, it provides students the opportunity to explore the interconnected relationships between multiple variables in a system and gain a deeper understanding of the underlying processes that drive a particular phenomenon (Ainsworth, 2008; Linn and Eylon, 2011). Computational models often have simulation features that allow the manipulation of variables in these models. These simulation features provide students with the ability to generate outputs, which they can then compare with data obtained from external sources, such as empirical studies or their own investigations (Lorenz, 2009; Damelin et al., 2017; Hassanibesheli et al., 2020). If the model's output does not match the external data, students can revise their model or question the validity of the data source. This iterative process of refining the inputs and relationships between variables can help students to improve their models over time (Weintrop et al., 2016; Shin et al., 2022).

Several approaches to computational system modeling exist, each with its own affordances that support learning about complex systems. Because this research focuses on static equilibrium and system dynamics modeling, we will focus on these two approaches.

The first, static equilibrium modeling, provides a computational representation of a system that consists of a set of variables linked by relationships that define how one variable influences another. Any change to an input variable is immediately reflected in new values calculated for each variable in the system (Shin et al., 2022). While enabling users to construct models with cause and effect relationships between system elements, the approach encourages students to go beyond simple linear causal chains and create models with long branching structures and mediating causes (Metcalf et al., 2000; Perkins and Grotzer, 2005); however, static equilibrium modeling does not consider time as a factor.

The second approach, system dynamics modeling, enables the representation of change over time and includes interactions between system components that include stocks and flows (Sweeney and Sterman, 2000; Ossimitz, 2002). Stocks refer to system components that accumulate or deplete over time while flows refer to system components that decrease or increase the amount in the stocks. System dynamic models allow the user to construct nonlinear interactions and structures such as feedback loops and to produce an output that represents change over time (Richmond, 1993, 1994; Forrester, 1994; Sweeney and Sterman, 2000). This approach addresses two major aspects of ST that the static equilibrium modeling approach cannot. The first aspect, feedback present in complex systems (Richmond, 1993, 1994; Forrester, 1994; Sweeney and Sterman, 2000) refers to any action that causes an effect back to the starting point of the action (Haraldsson, 2004). For example, an increase in greenhouse gasses (including methane) causes an increase in global temperatures. Warmer temperatures cause the permafrost in Earth's Northern regions to thaw. The thawing of the permafrost causes the release of methane, which further adds to the rise in global temperatures. This in turn exacerbates the thawing of the permafrost, which releases more methane to the atmosphere, and so on. The second aspect addresses how a system can change over time. Many phenomena require the consideration of change over time in which a time lag between the cause and effect exists. In some cases, the delay is negligible, as in certain chemical reactions while in others, the time delay is thousands or millions of years, as in evolution or the formation of a canyon (Kali et al., 2003; Assaraf and Orion, 2005; Meadows, 2008).

Researchers have studied students' use of static equilibrium models constructed to support sensemaking of scientific phenomena (Metcalf et al., 2000; Bielik et al., 2018; Shin et al., 2022), and system dynamics modeling (Eidin et al., 2023), but have not tested the use of both in the same curriculum context. Both static equilibrium and dynamic modeling approaches involve applying aspects of ST. Although using system dynamics has the potential to engage students in additional ST aspects, such as identifying feedback and framing problems in terms of change over time, it does not guarantee that using a system dynamics approach gives rise to different reasoning and growing causal complexity. Despite its potential, constructing system dynamics models remains challenging and it is not clear to what extent their use can benefit students compared to other approaches (Mandinach, 1989; Sweeney and Sterman, 2000; Eidin et al., 2023).

In this work, we investigate the complexity in students' explanations from an ST perspective as they construct and interpret static equilibrium and system dynamics models. In addition, we examine if static equilibrium models, which engage students in cause and effect reasoning but are considered simpler and more straightforward, could serve as a scaffold for constructing dynamic models that include feedback and thinking in terms of change over time, two of the most challenging aspects of ST.

3. Research question

How do students' explanations of static equilibrium and system dynamics models reflect aspects of systems thinking as indicated by the presence of various levels of complexity in multiple dimensions of causality?

4. Context

4.1. Curriculum

The present study was part of a six-week project-based learning chemistry unit that incorporated five investigations. The unit was designed to align with the Next Generation Science Standards (NGSS) performance expectations HS-PS1-3, "Plan and conduct an investigation to gather evidence to compare the structure of substances at the bulk scale to infer the strength of electrical forces between particles" and HS-PS3-2, "Develop and use models to illustrate that energy at the macroscopic scale can be accounted for as a combination of energy associated with the motion of particles (objects) and energy associated with the relative positions of particles (objects)" (NGSS Lead States, 2013). The study took place in a school setting, where students participated in two to three lessons per week, each lasting 80 min.

The unit was centered around a driving question: 'Why do I feel colder when I am wet than when I am dry?' In an introductory activity, students engaged in a tactile experience by placing droplets of water, ethanol, and acetone on their hands, followed by a group discussion to generate questions and hypotheses using a driving question board (Weizman et al., 2008). To facilitate the process of defining the key components underlying the phenomenon, students worked in small groups of three to four members to develop paper-pencil models, depicting the interrelationships among the variables. This step served as a foundation for a subsequent discussion comparing and contrasting the relative strengths and limitations of paper-pencil versus computational models. Students were introduced to the affordances of computational models, such as their ability to simulate and validate models using real-world data.

After the aforementioned discussion, students were instructed to represent their paper-pencil models as a static-equilibrium model using SageModeler, a free web-based modeling tool to facilitate both static equilibrium and system dynamics modeling (Damelin et al., 2017). Since students had some experience in building static equilibrium models using SageModeler during a previous unit, they were provided with a brief exercise to refresh their memory before constructing models to address the driving question.

Throughout the unit, students took part in various learning experiences, such as conducting hands-on experiments, working with computer simulations, and analyzing real-world data, which they used to iteratively revise their models. Initially, the focus of the unit was on modeling what factors would affect the evaporation rate and "coldness" of an evaporating liquid. These concepts were appropriately modeled using a static equilibrium approach. For example, an increase in intermolecular attractions between the molecules of a liquid would mean a decrease in evaporation rate and a decrease in the "coldness" felt when the liquid evaporated from your skin. Students completed an activity where they used sensors to measure the change in temperature over time, creating a cooling curve for each liquid. This activity led to a plenary discussion on the limitations of static equilibrium models in representing changes over time, as illustrated by the evaporative cooling processes, and created a need for a system dynamics modeling approach.

To support students in constructing dynamic models, they completed an introductory tutorial, which guided them in constructing a simple system dynamics model of their own while learning about the unique features of system dynamics modeling. After that experience, students built a dynamic model to address the driving question while considering the change over time of components in the system.

To validate their system dynamics model, students compared the simulation output from the dynamic models with their experimental results. This process allowed students to test the validity of their models and refine them.

The phenomenon of evaporative cooling presents significant challenges from an ST perspective. Understanding why one feels colder when wet than when dry requires a high level of performance in all dimensions of causality. The transfer of kinetic energy to potential energy, a dynamic process that affects multiple components in a system simultaneously, is a fundamental aspect that must be considered (Chen et al., 2014). In addition, a comprehensive mechanism should address the microscopic and macroscopic entities involved in the process, explaining how interactions between intermolecular forces result in emerging patterns (Ben-Zvi et al., 1986; Dori and Hameiri, 2003; Krist et al., 2019). Moreover, the cooling effect that emerges as a result of the random movement of molecules requires a departure from the use of linear causal reasoning and the attribution of a central causal agent. Research demonstrates that explaining emergent properties at the macroscopic level as a result of interactions at the microscopic level is extremely challenging (Chi, 2005; Tümay, 2016).

The exponentially shaped cooling curve resulting from evaporation cannot be explained by a simple linear cause and effect mechanism. Rather, it involves feedback, which is a prominent ST

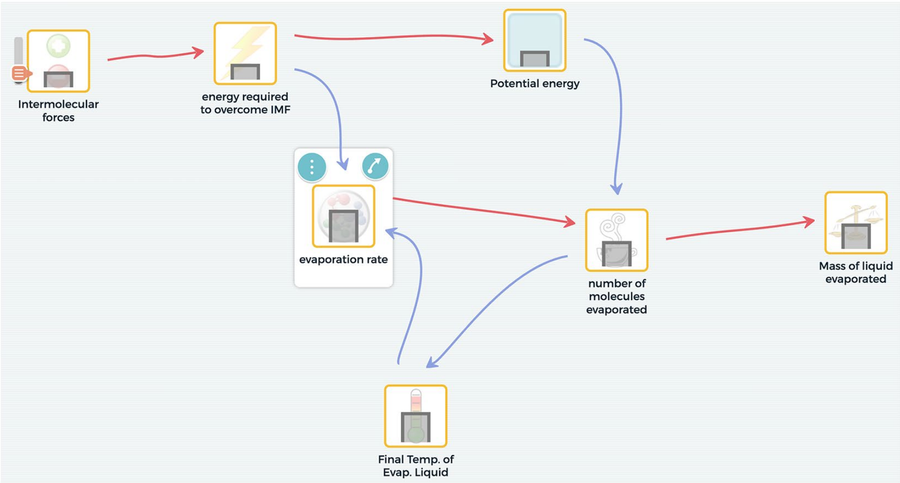

FIGURE 1
An example of a static equilibrium model constructed by students JU and TR. The nodes represent variables. The red and blue arrows represent a causal relationship between two variables. Red arrows represent a relationship in which an increase in one variable causes an increase in the other. Blue arrows represent a relationship in which an increase in one variable causes a decrease in the other.

aspect. The shape of the graph is also a result of the random movement of particles which accounts to an uneven distribution of kinetic energy among the molecules. Molecules with the highest kinetic energy leave the system first, causing the average kinetic energy (and thus temperature) to drop, lowering the evaporation rate. This feedback causes the liquid to evaporate and cool quickly at first, but over time both evaporation rate and cooling slow down as more molecules with the highest energy leave the system. However, explaining such behavior through feedback mechanisms has been documented as particularly challenging for students (Haraldsson, 2004; Tripto et al., 2013). Further details about the unit and the implementation of the evaporative cooling phenomenon using SageModeler can be found in Shin et al. (2022).

Figure 1 shows an example of an appropriate static equilibrium model of the evaporative cooling phenomenon. Figure 2 shows an example of an appropriate system dynamics model of the same phenomenon. The static equilibrium model represents an outcome behavior that accounts for why different liquids have different degrees of "coldness" as they evaporate from the skin at different rates. For example, one can notice in Figure 1 the intermolecular forces variable eventually affects the mass of the liquid evaporated and the final temperature of the liquid. Figure 2 shows a system dynamics model simulation output in which temperature and evaporation rate steeply drop at the beginning and then taper off in an exponential decay trend. This behavior requires the construction of a feedback relationship.

4.2. SageModeler

SageModeler[1] is a web-based open-source tool designed to support student learning by facilitating engagement in ST through constructing, evaluating, revising, and using models (Damelin et al., 2017). SageModeler allows students to construct static equilibrium and system dynamics models. The tool has two major modeling affordances: representation of variables and relationships and supporting model validation.

4.2.1. Representation of variables and relationships

SageModeler allows learners to represent components of the system as nodes in a system diagram. The nodes represent variables that are linked together, forming a visible network of cause and effect relationships. For example, consider the evaporative cooling phenomenon. In a static equilibrium model, one can set relationships in which an increase in intermolecular forces causes an increase in the energy required to overcome the intermolecular forces (IMFs) (Figure 1). In a system dynamics model, with one variable representing 'amount of liquid' and another representing 'amount of gas particles,' the user can set a different type of relationship, called a transfer link, to represent a flow from the liquid state to the gas state (Figure 2). By focusing on an explicit representation of the components and their relationships, SageModeler provides an accessible way for students to create an instantiation of their conception of the system.

To scaffold students in developing system models, SageModeler includes pull-down menus and graphs that students set to describe semi-quantitatively how one variable influence another. This eliminates the need for students to write complex mathematical equations or learn how to code, thus reducing cognitive load (Metcalf et al., 2000). We are not arguing that the use of mathematical equations or programming is not important for 21st century citizens; however, a viable strategy for making computational modeling more accessible is to reduce such barriers. In SageModeler, the relationship setting appears in the form of a sentence, such as, 'An increase in [variable X] causes [variable Y] to increase by *about the same.*' To define the relationship, students choose words with associated graphs.

1 https://sagemodeler.concord.org/

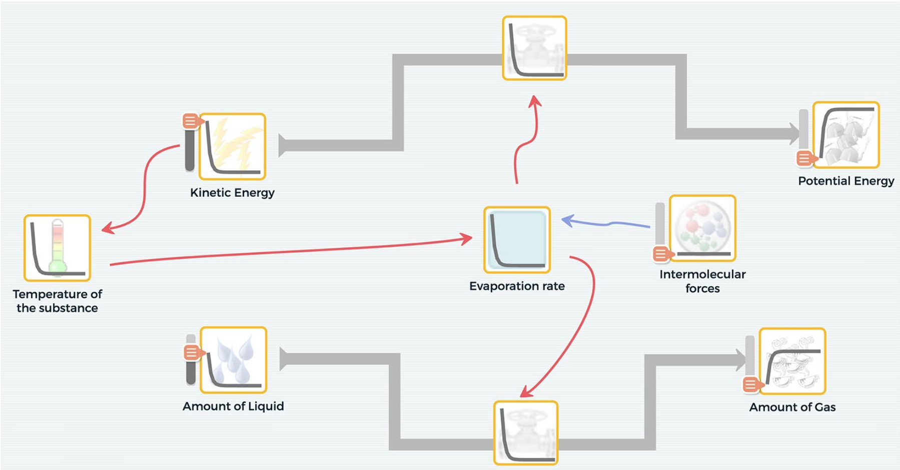

FIGURE 2
An example of a system dynamics model, which allows learners to set variables that accumulate over time and set the rate of flow between them. The simulation output produces mini-graphs inside the nodes, which represent change over time.

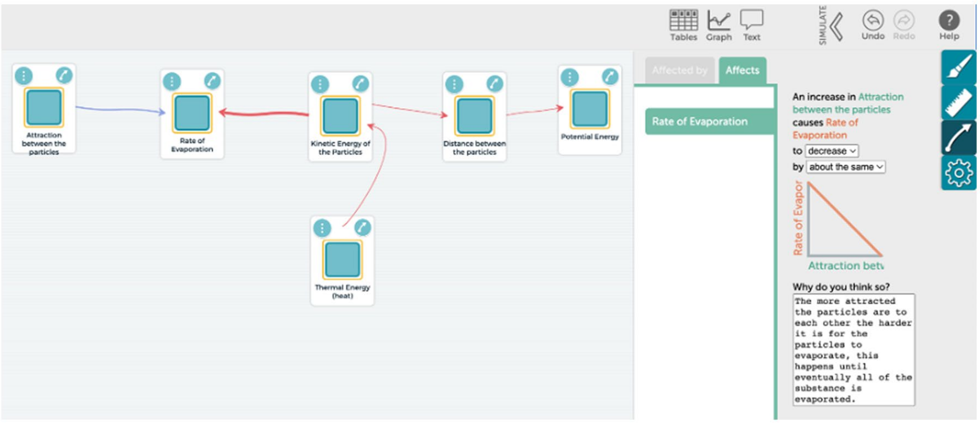

FIGURE 3
Users can set both the direction (increase or decrease) and the magnitude (about the same, a lot, a little, more and more, less and less) of relationships between variables in SageModeler.

For example, a linear graph is associated with the *about the same* relationship while an exponential graph is associated with the *more and more* relationship (Figure 3).

4.2.2. Supporting model validation

SageModeler allows users to simulate their model and test it by comparing their model behavior to real-world data. SageModeler facilitates that comparison by integrating the Common Online Data Analysis Platform (CODAP), which offers graphing and data analysis tools (Finzer and Damelin, 2015) and supports data imported from various sources. Students can import real-world and experimental data or output from other expert models and compare it to data generated from a SageModeler simulation. The software allows users to create graphs from various datasets and make decisions about the validity of their model.

4.3. Participants

Twenty-six 10th grade students from two chemistry classes in a magnet school from a rural–urban fringe district in the Midwestern U.S. participated in this study. Each class consisted of 24 students. The students were selected from the two classes, one taught by Mr. H, a chemistry teacher with 15 years of experience, and the other one taught by Mr. M, a chemistry and environmental science teacher with 6 years of experience. The sample, representative of the two classes, included 12 female and 14 male students, with a mixture of high- and low-achievers. The sample of participants was a convenience sample, based on students' and their parents' agreement to participate in human subject research. No data was collected on the students' socioeconomic background. Among the participants, two identified as Black, one as Asian, and the rest as White. Both teachers had prior experience using SageModeler and teaching both modeling approaches in their classes, although in a different context than the evaporative cooling unit. Mr. H and Mr. M had several meetings with the authors to walk through the activities and experiments in the unit and to discuss strategies for supporting students in constructing models using SageModeler. These meetings, which totaled seven hours, served as a preparatory step before the start of the unit.

5. Methodology

To answer the research question, we utilized two primary sources of data: student interviews and screencasts. The interviews served as the main data source, enabling us to compare the differences in students' explanations as they used both modeling approaches to explain evaporative cooling. The screencasts enabled a valuable insight into students' reasoning as they constructed models using each modeling approach. We utilized both the screencasts and interview transcripts to capture student reasoning and application of ST through the analysis of dialog and discussion.

5.1. Interviews

Student interviewees included 11 students, 5 female and 6 male, with each interview lasting 45–60 min. Students were asked to explain the phenomenon as they walked the interviewer through their static equilibrium model and then their system dynamics model. These interviews were semi-structured and included questions such as "Can you walk me through your model?" and "what does your model tell us about the evaporative cooling phenomenon?." The full interview protocol can be found in the Supplementary material. During the interview students were shown their models on a laptop; their responses to questions and references to their model were recorded. The interviews were fully transcribed. Conducting interviews in which students walk the interviewer through their model has been shown to be an efficient strategy to elicit students' understanding and reasoning (Schwarz et al., 2009; Eidin et al., 2023; Stephens et al., 2023). We coded and analyzed students' utterances that followed questions asking them to use their model to explain the evaporative cooling phenomenon.

Interviews were analyzed using the dimensions of causality framework described by Perkins and Grotzer (2005), as it provided a means to assess the complexity of students' explanations of the evaporative cooling phenomenon and make a fine-grained differentiation between linear causal explanations and more complex types of explanations that address ST aspects. We applied three of the dimensions of the framework (*agency*, *interactive pattern*, and *mechanism*). We established that only two levels of the *probability* dimension were applicable in the context of the phenomenon, and during the coding and analysis of the interview data, we found that the *probability* dimension exhibited significant overlap with the levels of the *agency* dimension. Therefore, we determined that the inclusion of the probability dimension did not yield any additional insights into the evaluation of students' reasoning, so we decided not to include it in our analysis. Table 1 provides an overview of the different levels of causal dimensions and specific examples of each level in the context of the phenomenon. Table 2 shows which levels of complexity of each causal dimension align with which ST aspects.

A scientific explanation for evaporative cooling using the causal dimension framework suggests that the *agency* in the system emerges due to the random collisions of particles. This leads to an uneven distribution of energy, creating a reentrant *interactive pattern*. In this pattern, particles with the highest kinetic energy overcome intermolecular forces and leave the system, which lowers the average kinetic energy of the remaining particles in the liquid phase. Additionally, as the particles overcome intermolecular forces to evaporate, the increased distance between attracting particles results in an increase in potential energy at the expense of some of the kinetic energy of the particles. This process results in a decreasing temperature and evaporation rate. The explanation also describes a mechanism that accounts for the random collision between particles and the conservation of mass and energy.

Two authors coded the data after two cycles of discussions. The first cycle had a 75% agreement. The second cycle had a 90% agreement. The coders discussed their differences to achieve 100% agreement. Further analysis conducted using Atlas.ti software, focused on differences in the dimensions of causality in students' explanations of the phenomenon in the static equilibrium and system dynamics models. Each dimension was analyzed separately, allowing for the detection of specific differences in students' reasoning between the two modeling approaches. Of note, the time allotted during the interviews for students to explain the phenomenon using each type of model was relatively equal for both models.

The following excerpt from student KY offers an example of how we utilized the dimensions of the causality framework when coding the interview transcripts.

> *"The average kinetic energy is transferring into potential energy. And the spacing of particles and IMF is affecting that transfer. Potential energy is the spacing of particles when you are talking about evaporation. So as the spacing particles increase, so is the potential energy. And then IMF is the opposite of that, because the IMF is the attraction between the particles and it wants to keep the particles together and it does not want them to space out. So, if the IMF is keeping the particles from spacing out, then if that was high, the particles would not be spacing out as much and there would be less potential energy. And then it's showing that the transfer from kinetic energy to potential energy affects the rate of evaporation."*

To code the excerpt above, we identified various dimensions of causality. It is noteworthy that not all dimensions are necessarily present in each student's remarks. To determine the level of *agency* in the student's explanation, we first identified the variables within the explanation: intermolecular forces, potential energy, kinetic energy, and the rate of evaporation. The student mainly focused on intermolecular forces as a significant variable affecting different variables in the system, albeit not as a central cause that accounts for the evaporative cooling phenomenon. Therefore, we assigned a level 2 to the *agency* dimension. Moreover, intermolecular forces were also identified as a mediating variable that regulates the transfer from kinetic to potential energy and, accordingly, the rate of evaporation. Consequently, we assigned a level 3 to the *interactive pattern* dimension. Additionally, since the student addressed the particle level and illustrated the impact of intermolecular forces on the flow of energy within the system, we assigned a level 6 to the *mechanism* dimension.

TABLE 1 Dimensions of causality (Perkins and Grotzer, 2005).

	Agency	Interactive pattern	Mechanism
Level 1	Central agents with immediate influence: One or a very small number of key factors fairly directly yield the result. May be interwoven with intentional causality. *Example in the context of the evaporative-cooling unit* "Adding thermal energy to the liquid causes evaporation. "	*Simple linear causality*: A impinges on, pushes, influences B. A is seen as not affected. (e.g., A pushes, pulls, initiates, resists, supports, stops B. A is typically seen as active as in pushing but can be passive as in resisting). *Example in the context of the evaporative-cooling unit* *"Thermal energy increases Kinetic energy and potential energy"*	*Surface generalization*: Simply describes the regularity under consideration in a generalized way ("When it is hot and it rains, there is lightning") or confuses correlation with causation. ("Heat and rain cause lightning") *Example in the context of the evaporative-cooling unit* *"When water evaporates of your hand your hand feels colder"*
Level 2	*Nonobvious central agents:* with a passive role or spatially delayed (e.g., intermolecular forces) *Example in the context of the evaporative-cooling unit* *"Adding thermal energy causes the increase in kinetic energy that causes the increase of space between particles, which causes an increase in potential energy. Intermolecular forces of the substance affect this process and have an impact on the rate of evaporation."*	*Multiple linear causality*: Multiple unidirectional causes and/or effects: Multiple immediate causes and/or multiple immediate effects; Domino casualties in which effects in turn become causes as in simple causal chains like A causes B causes C or branching patterns; Necessary and sufficient causes, etc. Often includes previously neglected agents of lower saliency in the causal story. *Example in the context of the evaporative-cooling unit* *"The amount of thermal energy increases the amount of potential energy which increases the rate of evaporation"*	*Token Explanation:* Some entity or phenomenon, intentional or not, made things come out that way. Entity/phenomenon's behavior parallels outcome, no real differentiation. | ("Static electricity makes it happen. ") *Example in the context of the evaporative-cooling unit* *"Thermal energy makes evaporation happen"*
Level 3	*Additive causes*: Cumulative effects over time (e.g., erosion). *Example in the context of the evaporative-cooling unit* *"There is a decrease in the temperature of the evaporating substance over time, as molecules with higher kinetic energy continue leaving the system."*	*Mediating cause:* At least three agents in play, M mediates the effect of A on B but not simply in the sense of A causes M causes B (e.g., M is a barrier to A affecting B, or a catalyst, or an enabling condition). *Example in the context of the evaporative-cooling unit* *"The transfer from kinetic energy to potential energy is controlled by the intermolecular forces of each substance as it dictates how much kinetic energy is required to eventually cause evaporation."*	*Functional explanation*: Explains in terms of purpose (Giraffes have long necks so that they can eat the leaves on the top of the tree.) *Example in the context of the evaporative-cooling unit* *"In order to evaporate a substance, you need more kinetic energy"*
Level 4	*Emergent entities and processes*-The actions of many individual agents at a lower level converge to give rise to new, complex patterns that are not easily anticipated based on the lower order actions *Example in the context of the evaporative-cooling unit* *"The random collisions between particles set the average kinetic energy of the system, that will affect overcoming the intermolecular forces between the particles of the substance that eventually result in evaporation."*	*Interactive causality*: Two-Way Causality: Interactive causation with a mutual effect (as in particle attraction); Mutual cause with two outcomes (as in symbiosis); Relational causality where the outcome is due to the relationship between two variables, (as in pressure or density differentials). *Example in the context of the evaporative-cooling unit* *"The molecules with the highest kinetic energy leave the liquid substance first, leaving the rest of the system with a low kinetic energy."*	*Commonplace elements:* Constructs explanations with familiar elements of the system in question rather than those underlying it. *Example in the context of the evaporative-cooling unit* *"The temperature of the substance is decreasing as it evaporates"*
Level 5		*Reentrant causality*: Simple causal loops as in escalation and homeostasis. *Example in the context of the evaporative-cooling unit* "As the molecules with the highest kinetic energy leave the liquid, average kinetic energy decreases, and as a result evaporation rate decreases, this process repeats itself causing evaporation rate to decrease over time."	*Analogical model:* System explains target phenomenon by analogy and analogical mapping (e.g., electricity as fluid flow).

(Continued)

TABLE 1 (Continued)

	Agency	Interactive pattern	Mechanism
Level 6			*Underlying mechanism:* Properties, entities and rules introduced that are not part of the surface situation but account for it (explanation refers to laws like conservation of mass and energy, collision of particles). *Example in the context of the evaporative-cooling unit "The increase of collisions between the particles means that the average kinetic energy increases. The growing collisions result in overcoming the interactions between particles."*

5.2. Screencasts

We conducted a screencast analysis of 10 groups engaged in constructing models using SageModeler. The groups were composed of the same individuals who participated in the interviews, along with their modeling partners. The screencasts recorded both the screen and voices of the participants, and varied in length among the different groups, with an average screen time of 120 min per group. The analysis focused on the discussions that transpired between the students, between the students and their teacher, and among students in neighboring groups. Notably, such episodes of discussion were infrequent and heterogeneous across the groups.

The analysis specifically targeted three aspects of ST: cause and effect, change over time, and feedback mechanism (Richmond, 1993; Orgill et al., 2019; Shin et al., 2022). To assess the level of cause and effect, we utilized the *interaction pattern* causal dimension from Perkins and Grotzer's (2005) framework. The levels of the *interaction pattern* provided insight into usage of cause and effect and feedback. To assess thinking in terms of change over time, we utilized the *agency dimension* with a focus on discussions about processes and aggregative effects. Particular attention was paid to terminology that indicated such thinking and included phrases such as 'first A happens then B,' 'it starts fast, but it slows down,' and 'over time as this change and goes down, the other changes and goes up.' We compared students' reasoning as reflected at the time they constructed their model and at the time they interpreted their model in the interview. We specifically looked for congruence between the type of reasoning students applied as they constructed the static equilibrium and system dynamics models and the reasoning they applied when they used their model to explain the phenomenon during the interview. For example, we examined correlations between discussions about change over time during the model construction process and the levels of dimensions of causality elicited in students' explanations during the interviews (Table 3).

6. Results

Student utterances were coded for levels of causal dimensions when providing explanations using their static equilibrium models and compared with those made when using their system dynamics models of evaporative cooling. The differences indicated by the level of causal dimensions revealed three distinct categories of students:

(a) those who demonstrated a consistently low level in dimensions of *agency* and *interactive pattern* in both modeling approaches, (b) those who maintained a high level of *agency* and *interactive pattern* in both static equilibrium and system dynamics models, and (c) those who showed an increasing level of complexity in dimensions of *agency* and *interactive pattern*, starting with a low level in the static equilibrium modeling approach and shifting to a higher level in the system dynamics approach.

To present a detailed differentiation between students' reasoning while using the two modeling approaches to explain the evaporative cooling phenomenon, we conducted separate analyses for each causal dimension. This fine-grained approach allows us to gain unique insights into students' application of the ST aspect in each modeling approach. The figures below provide a visualization of the level of the three causal dimensions as elicited from students' explanations during the interview as well as the number of utterances assigned to each level. The different color of the dots in the figure indicates the category each student fell under; consistently low, consistently high, and increasing in complexity. In the following sections, we discuss the results for each dimension.

6.1. Agency

According to the patterns illustrated in Figure 4, 90% of the students' utterances who utilized their static equilibrium models to explain the evaporative cooling phenomenon, demonstrated a lower level of complexity in the agency dimension. It was the maximum level achieved for 9 out of 11 students during the interviews, as opposed to when they used system dynamic models. In the system dynamic model, 64% of students' utterances confined themselves to a lower level.

Levels 1 or 2 were used as cutoffs for determining lower levels as they both describe simplistic agency.

Figure 4 shows students falling into three groups as previously mentioned: one student who's max utterances were high for both modeling approaches (ER), five students who demonstrated a consistent lower level in both modeling approaches (CA, GR, LU, TR, TY), and four students who exhibited an increasing level of complexity

TABLE 2 An alignment between higher levels of complexity of causal dimensions and ST aspects.

Higher levels of causal dimension		Alignment with ST aspects
Agency	Additive causes	Aligns with thinking in terms of change over time, which includes the recognition of time-related patterns within and across the system (Tripto et al., 2013). It also entails the determination of the time frame relevant to the phenomenon under concern (Richmond, 1993; Sterman, 2002)
	Emerging entities and processes	Aligns with considering an explanation that addresses the interactions between individual components within the system which results in a behavior different from the components' properties (Chi et al., 2012; Tümay, 2016).
Interaction pattern	Reentrant causality	Aligns with considering a feedback mechanism in which the interaction between system components results in an effect that loops back, causing a change in the magnitude of that effect (Wilensky and Resnick, 1999; Haraldsson, 2004).
Mechanism	Underlying mechanism	Aligns with thinking across levels (Wilensky and Resnick, 1999), which includes the consideration of components and laws that underlie the emergent behavior and those that are manifested in it.

TABLE 3 List of students who participated in the screencasts and interviewees.

Screencasts	Interviewees
KY and AD	KY
BE and AL	BE
CH and SU	CH
KA and MA	KA
ER and AU	ER
TR and JU	TR
CA and NA	CA, NA*
TY and BR	TY
LU, FR, and DR	LU
GR and AN	GR

*Students were interviewed separately.

when explaining the phenomenon using system dynamics models (BE, CH, KA, KY). The increase in levels refers to explanations that address aggregative effects and emergent behavior which align with these particular aspects of ST.

The data suggests that the use of system dynamics models increases the likelihood of students moving from a view that emphasizes a single prominent factor as the central agent affecting all other variables to a view that recognizes the cumulative effects of multiple factors over time.

Figure 5 shows the total number of utterances within each level of the *agency* causal dimension. We interpret this graph as indicating that the system dynamics model approach, (1) reduces the tendency to explain the phenomenon with a central component that has an instantaneous effect on the system and (2) encourages explanations with higher levels of complexity that consider accumulation over time and an emergent behavior.

Next, we present student quotes to illustrate the different levels of the *agency* causal dimension as revealed in the context of this research.

6.1.1. Level 1: salient central agent

GR: "*I would say the key variable would probably be the temperature because we determined that thermal energy was like the starting point of evaporation. So, then that would be like the main thing.*"

In the statement above, GR posits that the addition of thermal energy to the system is the primary variable responsible for initiating the evaporation process and, in turn, induces a cooling effect. In this sense, thermal energy serves as a salient central agent, warranting an evaluation at level 1.

6.1.2. Level 2: non-obvious central agents with long causal chains and branching structures

BE: "*So as intermolecular force increases, the time for evaporation also increases. And then you have the amount of the substance. Obviously, the more substance you have, the longer it will take to evaporate. And then you have the kinetic energy. So an increase in kinetic energy of the substance causes the time for evaporation to decrease. Also, we said the same for potential energy. Because potential energy is a measure of energy, when the particles are getting farther apart, that means that they are more likely to evaporate.*"

BE's explanation of her static model is characterized by individual cause and effect relationships and shorter causal chains, rather than a prominent variable that directly influences a specific output. Due to the absence of a salient central agent and a more complex causality relationship considering the influence of different components in the system on each other, this explanation is evaluated at level 2.

6.1.3. Level 3: additive causes, causes with cumulative effect over time

KY: "*The average kinetic energy should decrease over time and then the potential energy should increase, which would increase the rate of evaporation.*"

KY describes the accumulating change over time for kinetic and potential energy as one type of energy transfers to another. Therefore, this explanation is evaluated at level 3.

6.1.4. Level 4: emergent entities and processes, interaction of system components at a lower level interacting that produces new behavior

CH: "*The particles that are being evaporated are taking away the kinetic energy of the surface area by bumping into each other and transferring the kinetic energy. Since they are bumping into water particles, they are just transferring kinetic energy. It's not like there if I put water on the table, it's not like the table's gonna evaporate with the water. It's just that the table is going to get cold. Like your hand got colder.*"

CH explains that the random collisions between particles eventually lead to an uneven distribution of kinetic energy that leads to the evaporative cooling phenomenon. Considering how random behavior of components in the system lead to an emergent behavior at the macroscopic level warrants this explanation at level 4.

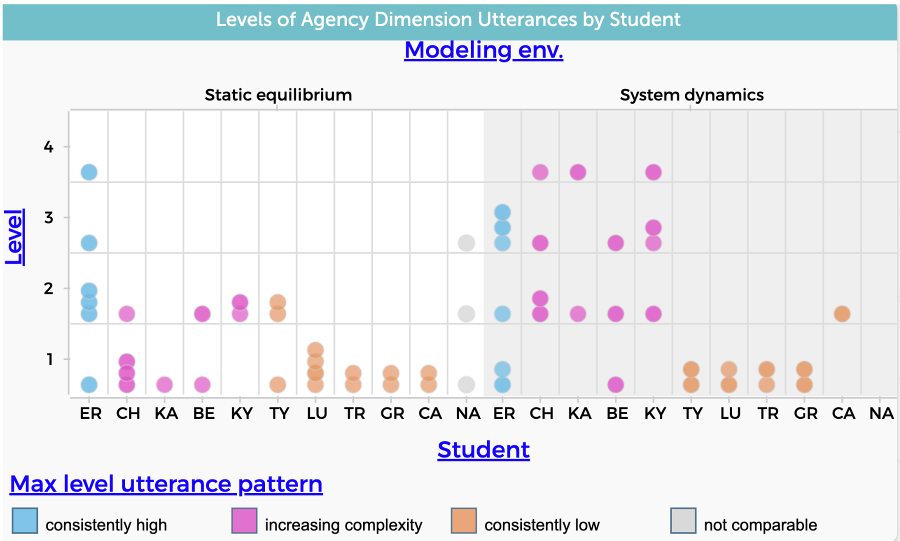

FIGURE 4
Frequency of students' utterances that refer to the agency causal dimension. The level variable in the y-axis refers to the four levels of complexity shown in Table 1. Each data point represents a single coded student utterance.

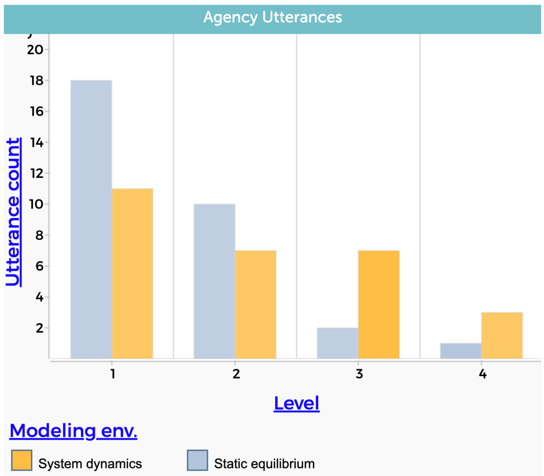

FIGURE 5
Students' level of agency causal dimension. Each column represents the total number of utterances in each modeling environment. The level variable stands for the level of complexity, from the lowest value of 1 to the highest value of 4.

6.2. Interactive pattern

According to the patterns illustrated in Figure 6, 73% of the students' utterances who utilized their static equilibrium models to explain the evaporative cooling phenomenon, demonstrated a lower level of complexity in the interactive pattern dimension. It was the maximum level achieved for 6 out of 11 students during the interviews, as opposed to when they used system dynamic models. In the system dynamic model, 48% of students' utterances were evaluated as lower level.

Levels 1 or 2 were used as cutoffs for determining lower levels as they both describe simple linear causal patterns.

Figure 6 shows students falling into three groups as previously mentioned: 4 students who's max utterances were high for both modeling approaches (ER,CH,CA, KY), 4 students who demonstrated a consistent lower level in both modeling approaches (GR, LU, TR, TY), and 2 students who exhibited an increasing level of complexity when explaining the phenomenon using system dynamics models (BE, KA). The increase in levels refers to explanations that demonstrate more complex causal patterns like those that address mediating variables and feedback, which align with aspects of ST. Of note, the same students who demonstrated low level in the interactive pattern dimension also demonstrated a low level in the *agency* dimension.

Five students exhibited a relatively high level of *interactive patterns* while using static equilibrium to explain the phenomenon (CA, CH, ER, KY, NA). A causal explanation that included a mediating variable characterized those explanations. Notably, the use of a system dynamics approach appeared to have a significant impact on the inclusion of feedback (Level 5) of four students' explanations.

Figure 7 shows the total number of utterances within each level of the *interactive patterns* causal dimension. It strengthens the notion that the system dynamics modeling approach is more conducive to addressing feedback mechanisms in students' explanations. In addition, the data presented reveals a reduction in the frequency of simple cause and effect utterances (Level 1) in the system dynamic context. It is interesting to note that many students included feedback as part of their explanations even if their system dynamics model did not include a feedback loop as part of the model's structure.

Next, we present student quotes to illustrate the different levels of the *interactive pattern* causal dimension as revealed in the context of this research.

6.2.1. Level 1: simple linear causality, A affects B

TY: "*So as the strength of the intermolecular forces increases, the amount of liquid particles also increases. And the amount of gas particles decreases because the stronger the intermolecular forces are in the liquid, the harder it is for the particles to get away.*"

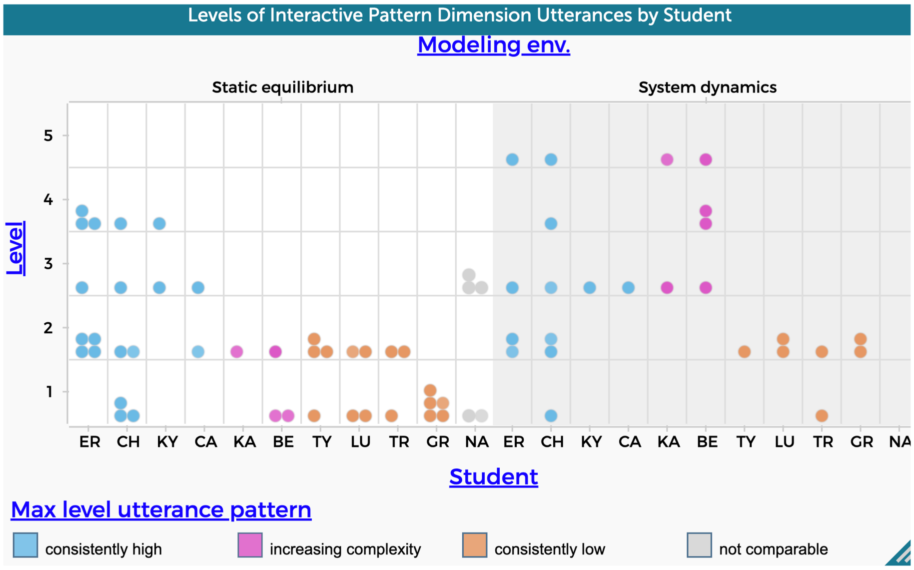

FIGURE 6
Frequency of students' utterances that refer to interactive pattern causal dimension. The level variable in the y-axis refers to the five levels of complexity shown in Table 1.

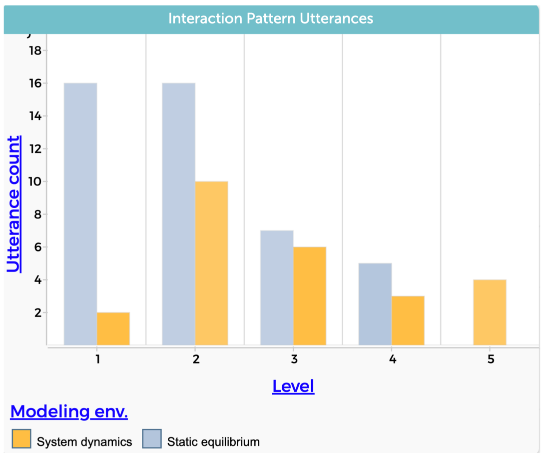

FIGURE 7
Students' level of interactive pattern causal dimension. The level variable stands for the level of complexity, from the lowest value of 1 to the highest value of 5.

TY provides a simple linear relationship in which variable A increases variable B and A decreases variable C, in which B and C are the amount of substance in liquid and gas phase, respectively. Given the explanation's simple linear cause and effect pattern, it was evaluated at level.

6.2.2. Level 2: multiple linear causality, A affects B affects C, may also include a branching pattern

TR: "*What our model is saying is that the more thermal energy in particles that you have, the more kinetic energy the particles have. And then when they move around more, they'll bounce around more, causing molecular forces to get weaker and increase the chances of breaking and then these breaking increases the amount of potential energy.*"

This student describes a pattern where A leads to B and then to C. TR characterizes intermolecular forces as extrinsic rather than intrinsic properties of a substance and explains that they become weaker due to particle collisions instead of being overcome by them. However, this simplified representation of a dynamic process does not accurately align with the scientific consensus and may result from the difficulty of representing a complex concept within a static equilibrium model. The rather detailed causal chain warranted a level 2 evaluation.

6.2.3. Level 3: mediating cause, M mediates the effect of A on B

KY: "*Right. So like I said earlier, the average kinetic energy is transferring into potential energy, and the spacing of particles and intermolecular forces is affecting that transfer.… So if the* intermolecular forces *is keeping the particles from spacing out, then if that was high, the particles would not be spacing out as much and there would be less potential energy. And then it's showing that the transfer from kinetic energy to potential energy is the rate of evaporation, which is affected by intermolecular forces.*"

KY refers to intermolecular forces as the mediating factor that controls the transfer from one type of energy to another. The ability to create a transfer link and set a relationship that mediates this transfer in the shape of a valve (Figure 3) supported students in including a mediating cause to their explanations. This explanation was coded at level 3.

6.2.4. Level 4: interactive causality, two-way causality

BE: "*So, as the particles gain kinetic energy, the higher energy particles are evaporating, and as they are evaporating, they are taking the kinetic energy with them, and that's decreasing the temperature of* *the water on your hands. So, when you have water on your hands, it makes you feel colder because that puddle of water is actually losing heat.*"

BE describes how the evaporation affects the temperature of the liquid remaining and how this in turn affects the evaporation. This description of interdependency warranted a level 4 evaluation.

6.2.5. Level 5: reentrant causality, simple causal loops

ER: "*So as the temperature goes down, the rate of evaporation is going to go down as well because it's going to have less high kinetic energy because the average kinetic energy is going down. Well, we are going to have some particles with high, some with low kinetic energy, but if the average going down as the molecules with high kinetic energy leave the system, that means you are losing higher kinetic energy molecules and you are not replacing them with anything. So it just keeps going down slower [temperature].*"

In this example, ER addresses the relationship between the distribution of kinetic energy within the particles of a substance and the rate at which its temperature decreases over time. Addressing the gradual change in the rate of evaporation ("keeps going down slower") distinguishes ER's explanation from BE's. ER describes a feedback mechanism where the leaving of particles with high kinetic energy from the system results in a decrease in the average kinetic energy within the system. This, in turn, leads to a reduction in evaporation and a slower decrease in temperature, thus causing a further slowdown in the rate of temperature drop over time.

6.3. Mechanism

The findings presented in Figure 8 reveal that most students reached the highest level in which they mention an underlying *mechanism* to explain the phenomenon in both modeling approaches. Yet a deeper examination of the explanations shows a difference between the static equilibrium and system dynamics context. In the static equilibrium approach, students explain the evaporative cooling phenomenon by referring to the particle level and describing interactions between molecules. In the system dynamics model approach, in addition to addressing the particle level, students also address underlying laws like the conservation of mass and energy. For example, in the context of static equilibrium modeling, NA says, "*Um, I think that because as the number of collisions increases, it increases the ability for the fastest particles to leave the system. So, as more collisions occur, more of those particles are going to be having that high speed, giving them the potential to leave the system in the form of vapor.*"

In the context of system dynamics modeling, CH says, "*Well, I believe kinetic energy does transfer into potential energy when it phase changes because energy cannot be created or destroyed, so when gas changes into a liquid and then into a solid, the energy has to be stored somewhere, and it cannot be stored as kinetic, so then it has to be stored as potential.*"

Besides those differences the patterns demonstrated in Figure 9 indicate no significant difference in the level of complexity with regards to the *mechanism* causal dimension between static equilibrium and system dynamics modeling approaches. Therefore, we do not provide examples of quotations for lower levels regarding the *mechanism* causal dimension as they were rare and insignificant.

To summarize the findings so far, we outline three salient patterns in the students' explanations pertaining to the *agency* and *interactive pattern* dimensions as they use the model they constructed in each of the modeling approaches to explain the evaporative cooling phenomenon. Additionally, we observed patterns in students' utterances within each dimension, with more complex levels of explanations being prevalent as students used their system dynamics model to explain the phenomenon.

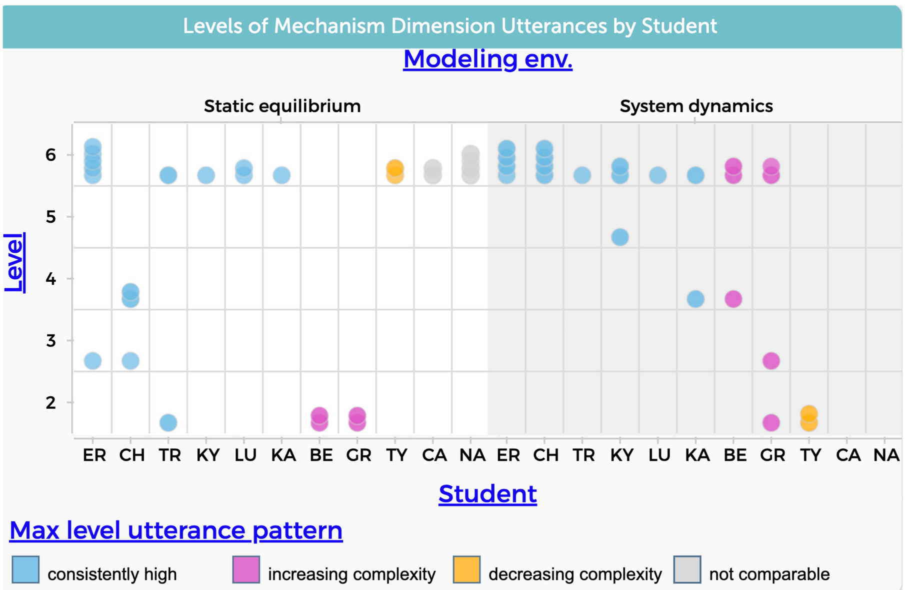

FIGURE 8
Frequency of students' utterances that refer to mechanism causal dimension. The level variable in the y-axis refers to the six levels of complexity shown in Table 1.

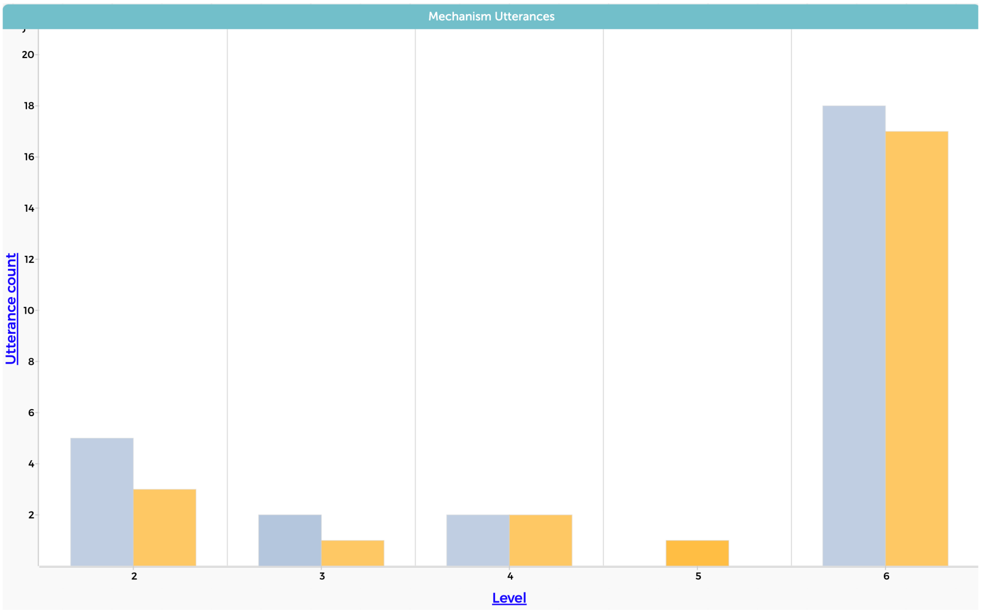

FIGURE 9
Students' level of mechanism causal dimension. The *y*-axis represents the frequency of the total utterances from the interviews.

6.4. Transitioning from static equilibrium to system dynamics modeling

The interviews solicited descriptions of the students' experiences during the transition from static equilibrium to dynamic modeling. Six of the 11 students reported a positive experience, stating that the shift from one approach to the other enabled them to better convey their understanding of the underlying processes. Following is a representative comment from a student.

KY: "*I think the whole time we were doing the static model, it was hard because we all wanted to explain it dynamically and we had to refine it to a static model where it wasn't changing over time. But then with the dynamic model, we got to show how it changed over time and explain the situation (the phenomenon). It makes more sense to look at a dynamic model because it's easier to look at a situation from this starting point and then this is the ending point. You can say like, you start with kinetic energy and then it transfers into potential energy. So, I feel like it's easier to understand a situation looking at a dynamic model and it was easier in some ways to put our ideas into it, so it helped [the transition from static equilibrium to system dynamic modeling].*"

The quote shows how student KY perceived the transition as supporting her in expressing her understanding of the phenomenon better in the dynamic model. She also describes a sense of frustration with the static equilibrium's limitations. Additionally, three students mentioned that the affordances of system dynamics modeling supported their understanding of the phenomenon. Below is a representative quote from student ER.

ER: "*But actually seeing the effect of intermolecular forces on the evaporation rate was a really big connector for me because I did not understand how it changes through time because at first, I thought the rate of evaporation was constant the entire way through the process.*"

The data analysis uncovered two recurring themes in the responses of students who reported positive attitudes about the transition. First, these students displayed a greater degree of sophistication in the *agency* and *interactive patterns* causal dimensions as evidenced by their interview responses. Second, the screencasts of these students showed that they included time-related variables, such as 'time,' 'time for evaporation,' and 'process of phase change,' while constructing their static equilibrium models. In many instances, the inclusion or exclusion of these variables was accompanied by discussions regarding limitations in accurately representing the evaporative cooling phenomenon, such as the phase change from liquid to gas or the transfer of kinetic energy to potential energy. A summary of these findings can be found in Table 4.

For example, KY and her partner integrated in their static equilibrium model variables they named 'time' and 'phase change.' When Mr. M approached them and asked about those variables, KY answered, 'We tried to represent the phase change.' When BE was asked by her peers about their static equilibrium model and the variable they named 'time for evaporation,' BE answered, 'We tried to represent the process of evaporation and the time it takes the substance to evaporate.'

At some point, Mr. M noticed that some students tried to represent a process in their static equilibrium models, so he addressed the whole class, noting, "*With the tool given to us, we cannot model a process. We can only model position. If you got things that are procedural, you may want to remove them. You cannot set up a relationship like A becomes B.*"

On the other hand, the students who did not perceive that the transition to a different modeling approach supported their understanding of the phenomenon showed a tendency to think of the phenomenon in a linear cause and effect fashion, as evidenced in their interviews and screencasts. CH and NA are a representative example of a group for whom the transfer to dynamic modeling was not sufficient to shift to a more complex explanation and model. The discussion during the construction of their static equilibrium model mostly concerned specific single relationships, even as the teacher was trying to get them to 'zoom out' and consider the overall interaction

TABLE 4 The table summarizes three criteria: (1) students' positive attitudes about shifting to system dynamic modeling as elicited in the interviews, (2) students' inclusion of a 'time' component during the construction of their static equilibrium models, (3) students' engagement in a discussion which addressed process or change over time during the construction of their static equilibrium models.

Students' name	Positive attitude about shifting to system dynamics	Time component in the static equilibrium model	Discussion about process and change over time
KY	+	+	+
BE	+	+	+
CH	+	+	+
KA	+	+	+
ER	+	+	+
JU	+	–	+
CA	–	–	–
NA	–	–	–
TY	–	–	–
LU	–	–	–
GR	–	–	–

Regarding the first criteria, the plus sign indicates at least one utterance in which students expressed a positive attitude toward the transition from static equilibrium to system dynamics modeling approach. Regarding the second criteria, the plus sign indicates at least one event in which students included a time related variable during the construction of their static equilibrium model. Regarding the third criteria, the plus sign indicates at least one episode in which students engaged in a discussion about change over time as they were constructing their static equilibrium model.

between the system's components. As they were working on their dynamic model, the pair continued to define linear causal chain relationships and interpreted the dynamic components (i.e., stocks and flow) in the system as cause and effect relationships.

While analyzing students' dialog and discussion in the screencasts that recorded the construction and revision of their models, we noticed how the limitations of static equilibrium modeling in representing simultaneous events created a confusion about setting relationships between variables. The following quote in which CA, NA, and ER have a discussion is a representative example for such a confusion (While working as a pair, CA and NA talk with ER, who is from a different group).

ER: *So you start off with your temperature affecting potential energy, but temperature does not directly affect potential energy.*

NA: *Yeah, it does.*

ER: *That's, well, I mean, temperature affects how far apart the particles are, which affects potential energy.*

NA: *No, because potential energy affects the spread of particles.*

ER: *Well, I mean, yes. So, temperature, how does it affect potential energy?*

NA: *I mean, looking at this yesterday when we put all that heat in it measured the potential energy increasing because of the temperature, it could be related to…*

ER: *I'm pretty sure that it does not affect the potential energy like it. I'm pretty sure temperature affects the spread of particles.*

CA: *Yeah eventually.*

ER: *I am pretty sure the spread of particles is affected by, no, potential energy is affected by the spread of particles.*

An analysis of this dialog from a causal dimension perspective reveals a rather low level with both the *agency* and *interactive pattern* dimensions. With regard to the *agency* dimension students perceive temperature as a salient agent serving as a precursor impacting the other variables in the system, hence aligning with a lower level of the *agency* causal dimension. Examining the *interactive pattern* causal dimension, it is apparent that students employ a linear causal mechanism to explain the increase in potential energy. The assumption of a single variable driving the behavior of the system with a simplistic linear reasoning impedes students' ability to consider simultaneous changes. Specifically, they overlook a simultaneous perspective in which kinetic energy converts to potential energy as it overcomes intermolecular forces. This dialog excerpt is an exemplar of how linear causal tendencies can constrain explanations of complex, feedback-oriented phenomena. It suggests that static equilibrium modeling may not be effective in breaking these patterns of thinking.

7. Discussion

Modeling is an essential practice within scientific disciplines, which is crucial to engage students from a young age (Gobert and Buckley, 2000; Matthews, 2007; Schwarz et al., 2009; Louca and Zacharia, 2012). However, modeling tools, particularly those with different computational modeling approaches, have distinct affordances that can support various learning objectives. Therefore, it is imperative to examine to what extent these affordances facilitate students' application of higher levels of causal complexity and ST to make sense of a phenomenon.

The present study addresses this need by comparing students' explanations of a phenomenon as they constructed and used two computational modeling approaches to comprehend evaporative cooling. Specifically, this study investigates the extent to which the static equilibrium and system dynamics modeling approaches support explanations that surpass simple linear causal reasoning and apply ST aspects, such as thinking in terms of change over time and identifying feedback. We specifically used the dimensions of causality framework to assess the application of ST in students explanations, as higher levels of dimension of causality align with ST aspects, and the identification of these allowed to assess the application of ST.

Based on our findings, the utilization of both static equilibrium and system dynamics models evoked variations in the rationales provided by students regarding the causal dimensions of *agency* and *interactive pattern* as they used the two modeling approaches. Notably, our investigation demonstrated that more complex levels of those dimensions were found in students' responses when employing system dynamics models compared to static equilibrium models. We do not believe that those results are due to students' gaining more experience in SageModeler as they progressed throughout the unit, as those students had prior experience with constructing static equilibrium models before the implementation of the unit. If anything, they were lacking more experience with system dynamics models.

Though the discrepancy in the level of explanations and the application of ST between the two modeling approaches does not seem surprising as static equilibrium modeling is not designed to support change over time, one must keep in mind that at the time students were interviewed they had already completed the unit, which included activities that aimed to support them in explaining the evaporative cooling phenomenon in terms of change over time. Also, no additional information was provided to them except the models they constructed during the unit. Hence, we did not expect such a divergence in students' explanations as our assumption was that the experience from the unit would have caused an overlay of the static equilibrium model explanations with higher level utterances. In that sense the findings are intriguing, because they show that each modeling approach prompts certain types of explanation and reasoning, with the use of system dynamics modeling more likely prompting explanations that address ST aspects. These findings align with prior empirical studies that have established the utility of system dynamics models in fostering reasoning that accounts for temporal transformations (Eidin et al., 2023).

The findings suggest that when utilizing either modeling approach, students interchangeably apply high and low levels of causality to explain phenomena. These results align with the cognitive theory proposed by Chi et al. (2012), which posits two competing causal schemas: direct and non-direct. The former is characterized by a linear narrative script while the latter is characterized by non-linear causal patterns. Notably, Chi (2005) and Chi et al. (2012) demonstrated that students can provide explanations based on both linear directionality and self-organization simultaneously. This theoretical framework corresponds with the work of other cognitive scientists who argue that two types of cognitive processing—one that is more intuitive and the other that is more logical—exist (Anderson, 1996; Kahneman, 2011). Our results corroborate these findings in cognition by demonstrating the presence of reductionist reasoning, which is based on a salient agent and simple linear causal chain, as well as a more complex reasoning that is based on thinking in terms of change over time and feedback. Based on these findings, we argue that a system dynamics approach has the potential to encourage a more complex causal schema of the phenomenon, which the static equilibrium model was unable to support.

The present study reveals that students who incorporated high level dimensions of causality into their explanations, and hence applied ST aspects while utilizing the system dynamics model, engaged in deliberations about change over time while constructing static equilibrium models. Conversely, students who did not incorporate such high levels did not engage in such deliberations. We suggest that the dynamic nature of the phenomenon and the requirement to represent it in a static equilibrium environment may lead to a cognitive dissonance for some students, as a static representation in which variables have an instantaneous effect on one another did not align with the consideration of the system's change over time. As such, shifting to a system dynamics approach may have reduced that dissonance. However, the factors that prompted such deliberations and the cognitive dissonance that some students experienced are unclear. One possibility is that the extensive time spent working on the static equilibrium models reinforced pre-existing tendencies to think in simple linear causal patterns, perpetuating a linear narrative schema.

This study demonstrates that the use of system dynamics models facilitated some students' ability to incorporate high levels of *agency*, such as including cumulative effects over time and addressing emergent behavior in their explanations. Such reasoning, based on the order that emerges from chaos and the random behavior of system components, is not intuitive and often conflicts with prevalent human reasoning across disciplines, which emphasizes salient components that instantaneously affect system behavior (Assaraf and Orion, 2005; Hmelo-Silver et al., 2007b; Chi et al., 2012). Our contribution to the field lies in providing evidence that system dynamics models can prompt students to consider both emergent behavior and change over time, thereby serving as a promising tool for engaging students in these aspects of system thinking.

We also found that both modeling approaches had the potential to elicit high level explanations with regards to the *interactive pattern* dimension with a high frequency of explanations of multiple linear causality. These results align with previous research that has demonstrated the ability of static equilibrium models to support and encourage multiple linear causality in students' explanations (Bielik et al., 2018; Shin et al., 2022). Our findings expand upon this previous work by demonstrating the affordances of system dynamics modeling in supporting students in considering a feedback mechanism. Users can represent feedback structures using both modeling approaches, and despite the fact that none of the students included a feedback structure in their static equilibrium or system dynamics models, their dynamic models prompted an explanation based on a feedback mechanism. The results lead us to conjecture that the model's output that represents change over time elicits more sophisticated causal mechanisms. This claim is based on research that argues that thinking in terms of change over time and accounting for a feedback mechanism are inextricably linked, as the feedback requires the consideration of time delays (Richmond, 1993; Haraldsson, 2004). We acknowledge that the limited amount of evidence collected does not support a substantive generalization; however, the evidence and findings do point to the potential of system dynamics models in considering feedback as an explanatory mechanism of the evaporative cooling phenomenon. In that sense, this work advances the field in supporting students in applying feedback mechanisms, a challenge that has been well documented (Haraldsson, 2004; Hmelo-Silver et al., 2007b; Martinez-Moyano and Richardson, 2013; Tripto et al., 2013).

Our findings also show no notable differences between the two modeling approaches regarding the *mechanism* causal dimension. This observation can be attributed to the design of the unit, which effectively integrated macroscopic and microscopic levels (Dori and Hameiri, 2003) and used various simulations that illustrate the behavior of particles. Additionally, the simulations allowed the students to explore abstract concepts such as kinetic energy, potential energy, and intermolecular forces, supporting students in understanding the underlying components that explain the system's behavior.

Our work also contributes to the field of chemistry education, as it addresses some of the questions posed by York et al. (2019) about the potential implications for integrating ST into chemistry education. For example, by analyzing students' level of the *agency* causal dimension in their explanation, we reveal that though the use of thermal energy as an external cause of the evaporative cooling phenomenon is prevalent, such misunderstanding can be mitigated by the use of a system dynamics modeling approach. An implication for chemistry education suggests that the use of system dynamics models can support students in focusing on the system's variables and distinguish those from external components students may use to make their explanation of the phenomenon more complex than necessary. Furthermore, we show that students' adopting thinking in terms of change over time, which has also been recognized as a significant component in integrating ST into chemistry education (Flynn et al., 2019; Orgill et al., 2019; York et al., 2019), is pivotal to understanding a phenomenon in which rate is integral. Therefore, we suggest that chemistry educators should be aware of the importance of thinking in terms of change over time, especially when exploring phenomena and concepts that relate to rate, such as chemical kinetics and equilibrium. Using system dynamics models could be a promising approach to meet those goals. Our work suggests that a promising avenue in supporting students in understanding such phenomena and concepts is to engage students in tasks that promote thinking in terms over time, and refrain from encouraging a reductionist approach based on simple cause and effect relationships that might hinder further progress.

7.1. Research limitations

We acknowledge that the sample size of students in this study is small, and, therefore, caution must be exercised when generalizing the findings to a broader population of students. The population of students was also unique as the research was conducted in a magnet school serving students who excel in science from 16 surrounding districts. Furthermore, we acknowledge that the order in which students were asked to use each modeling approach, starting with a static equilibrium and then moving to a system dynamics model, might have an impact on the results. It might be that starting with a system dynamics modeling approach would impact students' ST in a manner that would render no discernable difference in their explanations when subsequently using their static equilibrium models. Additionally, this study was conducted within the context of the evaporative cooling phenomenon, which involves understanding the emergence of phenomena from microscopic-level interactions among entities. It is possible that different phenomena involving interactions between macroscopic entities, such as those related to ecosystems or geology, may have yielded greater opportunities for the application of ST aspects in both modeling approaches. While the teachers played a crucial role in facilitating students' understanding, this study did not focus specifically on the teachers' supporting strategies due to the limited scope of the research. Moreover, both teachers deviated from the curriculum, particularly by the time the students constructed their dynamic model. A greater adherence to the curriculum may have resulted in a higher proportion of students demonstrating complex ST aspects.

7.2. Conclusion

Our study provides evidence of both modeling approaches supporting students in ST, though to different extents. We showed that system dynamics modeling promotes more complex aspects of ST compared to static equilibrium modeling. Our findings demonstrate that system dynamics modeling can support students in shifting from a reductionist, centralized view, in which a major variable dominates the system's behavior or a simple linear cause and effect relationship accounts for the whole system's behavior to a more comprehensive perspective that considers the dynamic changes of variables over time and the emergence of patterns from interaction between system's components. Our contribution lies in elaborating on the potential of using system dynamics models to enhance ST learning and in raising new questions about the use of tools that support cause and effect reasoning as scaffolding for applying ST aspects. We also show evidence that engaging students in linear causal relationships in a context of which a phenomenon is experienced as evolving over time may hinder further application of ST aspects. Given that forming causal relationships is fundamental to science education, our findings open an avenue to further investigation regarding the necessity of striking a balance in which linear causal thinking does not hinder the application of ST aspects.

Moreover, further research is needed to explore the potential of system dynamics modeling in different contexts, including those that exclusively involve macroscopic entities as well as those that involve both macroscopic and microscopic entities. Finally, more research is necessary to better understand whether scaffolding students' development of complex reasoning skills can facilitate their future adoption of ST practices.

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 Michigan State University IRB approval. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

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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.

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Supplementary material

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EDITED BY
Orit Ben Zvi Assaraf,
Ben-Gurion University of the Negev, Israel

REVIEWED BY
Watcharee Ketpichainarong,
Mahidol University, Thailand
Karel Vojíř,
Charles University, Czechia
Annette Upmeier Zu Belzen,
Humboldt University of Berlin, Germany

*CORRESPONDENCE
Katherine M. Miller
✉ kmiller@concord.org

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Teaching complexity in biology through agent-based simulations: the relationship between students' knowledge of complex systems and metamodeling knowledge

Katherine M. Miller[1]* and Susan A. Yoon[2]

[1]Concord Consortium, Concord, MA, United States, [2]Graduate School of Education, University of Pennsylvania, Philadelphia, MA, United States

Real-world complex systems research seeks to understand how systems in the world can follow the same rules of complexity. Scientists have found similarities in processes—such as self-organization, micro-to macro-level emergence, and feedback loops—in seemingly disparate phenomena such as the spread of infectious diseases and how traffic patterns are formed. Our project, BioGraph 2.0, was developed to respond to the issue of students' disjointed understanding of biology due to the fragmented nature of how high school biology is taught in high school classrooms. We hypothesized that by framing multiple biology concepts through the lens of complexity using dynamic simulations, or models featuring complex systems processes, students would be able to see complex systems as a unifying concept throughout biology. We built a series of units modeling phenomena on biological concepts such as gene regulation, ecology, and evolution using an agent-based modeling tool called StarLogo Nova. While previous research over the last decade of this project has highlighted students' growth in complex systems understanding, in this study, we explored the relationship between complex systems and agent-based models. We investigated pre and post intervention data from over 300 high school students to determine how their metamodeling knowledge influenced their understanding of complex systems. Through a regression analysis, we demonstrate that growth in students' modeling understanding significantly predicted growth in complex systems understanding. We further triangulate our findings with interview data from students who highlight the importance of the modeling tool to support their complex systems learning.

KEYWORDS

complex systems, modeling, agent-based simulation, biology, metamodeling knowledge

1. Introduction

The natural and social world that surrounds us is made up of systems that follow the rules of complexity (Servedio et al., 2014; Camazine et al., 2020). *Complex systems* can be defined as macrolevel patterns or structures that emerge from the activity of microlevel interacting agents (Yoon et al ., 2018a). Researchers from different disciplines have noted that, regardless of the kinds of agents (e.g., predator and prey) and the ontological phenomenon under investigation (e.g., ecosystems), complex systems are composed of web-like structures in which individuals follow rules (e.g., wolves eat rabbits; Chi et al., 2012; West, 2014; Bar-Yam, 2016). Complex systems also have intricate interdependencies and structures that exist at different scales (e.g., trophic levels in ecosystems; Bar-Yam, 2016). Because of this web-like nested structure, information travels in nonlinear ways, which makes understanding cause and effect in complex systems behaviors challenging (Grotzer and Tutwiler, 2014). Moreover, often the dynamics that fuel complex systems behaviors (e.g., feedback loops and self-organization) are hidden and take place over large time spans (e.g., evolution) or spatial scales (e.g., climate change), which limits what we can understand about the whole system at any point in time or place (Grotzer and Tutwiler, 2014).

It is not surprising then that students in K–12 education harbor misconceptions about systems. A number of empirical studies have shown that they tend to adopt a linear approach when thinking about the relationships among system components rather than recognizing their nested non-linear nature (Sweeney and Sterman, 2007; Gotwals and Songer, 2010; Riess and Mischo, 2010). For example, Gotwals and Songer (2010) found that students struggled with reasoning about how a disruption in one part of a food chain could impact changes in another part of the food chain that was not directly connected to it. These indirect relationships, as Chi et al. (2012) argue, are hard to comprehend because the perceptual apparatus through which we observe phenomenon is limited to the information about the system we have access to at a particular point in time. Another common challenge that researchers have discussed is the tendency for students to attribute an outcome to a central agent or cause (Penner, 2000; Taber and García Franco, 2010; Levy and Wilensky, 2011). Students are unable to recognize that often control in systems is decentralized and that structures or behaviors at macro levels emerge from micro-level system activities. For example, ecosystems are able to stay in equilibrium (macro-level pattern) because of the combined activities of micro-level components (e.g., predator–prey interactions). But even more fundamentally, in a series of studies, Ben-Zvi Assaraf and colleagues have found that students often struggle to accurately identify the components that comprise a system and how those components are interrelated or exist as an integrated whole (e.g., Assaraf and Orion, 2010; Assaraf and Orpaz, 2010; Assaraf and Knipples, 2022).

To address these learning challenges, researchers have posited that computational modeling tools such as agent-based simulations could provide access to structures and behaviors of systems to support sense making and have been researching their uses and affordances (Wilensky and Jacobson, 2015; Wilensky and Rand, 2015; Yoon et al., 2018a; Mambrey et al., 2022; Yoon, 2022). A majority of this research has examined learning of biological systems. In our recent systematic review of complex systems research in K–12 science education, we found that topics within the field of biology were investigated in 83% of studies (Yoon et al ., 2018a). Within these studies, agent-based simulations have been used to represent the complexity of biology systems in a more tangible and accessible format for students to explore complex systems thinking (Hmelo-Silver et al., 2017; Markauskaite et al., 2020; Housh et al., 2022; Jacobson and Wilenski, 2022; Yoon et al., 2022).

Models and modeling approaches have, in fact, received a great deal of attention in science education research due to their importance in conducting real-world scientific inquiry (NGSS Lead States, 2013). However, while learning and participation outcomes through the study of computational complex systems models have been generally understood to be positive, we found that only two studies in our systematic review (Yoon et al., 2018a) explored the relationship between instructional approaches that use complex systems models and student learning of complex systems. However, there is extensive research into how students conceive of models (e.g., Nicolaou and Constantinou, 2014; Nielsen and Nielsen, 2021). While content knowledge is important for working with models, so is metacognitive knowledge of models or metamodeling knowledge (Schwarz et al., 2009; Upmeier Zu Belzen et al., 2019; Chiu and Lin, 2022). This study explores how the instructional approach of agent-based models to represent complex systems afforded change in students' metamodeling and complex systems knowledge and the relationship between the two.

The research reported here builds on more than a decade of work in which we have explored the use of computational complex systems models to support teaching and learning in high school biology. We built a series of units modeling phenomena of biological concepts such as gene regulation, ecology, and evolution using an agent-based modeling tool (described in more detail below). In this program of research, we have explored various educational goals such as designing curriculum and instruction to support complex systems and biology learning (Yoon et al., 2016), professional development for classroom instruction (Yoon et al., 2017), building teachers' social capital for complex systems teaching (Yoon et al., 2018b), a learning progression for complex systems understanding (Yoon et al., 2019a), and supports for teacher community building to scale complex systems PD in online platforms (Yoon et al., 2020a,b). In this study, we address the need articulated in the review by Yoon et al. (2018a) for more studies that investigate the relationship between instructional approaches and student learning outcomes. Specifically, we investigated how students' understanding of biological models using the modeling tool influenced their understanding of complex systems. To this end, we ask the following questions:

1. To what extent did biology students' complex systems and modeling knowledge change over time?
2. To what extent is there a relationship between students' modeling knowledge and their complex systems understanding for biology systems?
3. What affordances of the modeling tool and process can explain this relationship?

2. Theoretical background

Knowledge and understanding of complex systems and scientific models are inextricably linked due to the nature of complex systems and the need to create models to understand and analyze them, however there is an additional need to understand how high school students perceive and utilize this link in building their complex systems knowledge. The Next Generation Science Standards (NGSS) emphasize the connection in combining the two into a single crosscutting concept, *systems and system models,* which is explained as "defining the system under study—specifying its boundaries and making explicit a model of that system—provides tools for understanding and testing ideas that are applicable throughout science and engineering" (NGSS Lead States, 2013, Appendix C, p. 1). As such, there is a need to explore how both complex systems and scientific models are conceived by students and how those conceptions might influence knowledge development across both areas and their combined real-world applications.

2.1. Dimensions of complex systems understanding

Within K–12 research, several conceptual frameworks have been applied to what has been generally called *systems learning* (Yoon et al., 2018a). Specifically in biology, three frameworks have been popular for providing the theoretical foundation to understand how students learn: (a) systems thinking; (b) components-mechanisms-phenomena (CMP); and (c) complexity from emergence. Briefly, *systems thinking* focuses on the interrelationships and interdependence of system structures, which first requires identifying the components that comprise the system (e.g., the boundaries) and then considering the dynamic relationships between the components (Assaraf and Orion, 2010; Assaraf et al., 2013). Thus, the focus is on understanding particular qualities of the system under investigation that are unique from system to system. Similarly, a CMP framing emphasizes components, connections, and behaviors that phenomenologically define a particular system (Hmelo-Silver et al., 2017). Researchers have investigated aspects of systems understanding in CMP categories, noting that instruction often only focuses on macro-level structural components (e.g., trees, oxygen) at the expense of learning about mechanisms or behaviors (e.g., photosynthesis, carbon cycle) that underpin the function of a system (e.g., Jordan et al., 2014).

The third characterization of systems learning—*complexity from emergence*—aims to apply common processes that fuel systems. Researchers from this tradition recognize that systems from within and between disciplines often exhibit similar characteristics (e.g., feedback loops, self-organization, nonlinearity) that happen in microlevel interactions to produce macrolevel patterns (Chi et al., 2012; Wilensky and Jacobson, 2015; Yoon et al., 2017). This framing of emergent behaviors from local (simpler) behaviors to global (more complex) structures has supported research in notable organizations, like the Santa Fe Institute, to investigate some of the worlds' most pressing problems such as disease epidemics and climate change. Our own work has taken this approach to learning about systems and has sought to understand how students reason through specific complex systems dimensions (Yoon et al., 2016, 2017) that include (a) the predictability of effects caused by small changes to the system, (b) the dynamism of the mechanisms and processes underlying the system, (c) the level of centralization of the organization of the system, and (d) the scale of the effects and capacities of the system (see Yoon et al., 2016 for more details). These four components are comprehended on a scale that ranges from, on one end, a clockwork framework of systems, in which systems are examined as individual parts, to, on the other end, a complex framework of systems understanding that acknowledges that the whole is greater than the sum of the parts. In other words, the properties of the whole complex system are properties that none of the parts have alone (Jacobson et al., 2011). In order for students to develop their understanding of complex systems, they must shift their ontological categories and move from a clockwork to a complex understanding of systems (Chi, 2005).

2.2. Scientific modeling and the importance of metamodeling knowledge

As the NGSS crosscutting concept *systems and system models* suggests, models and modeling are a vital part of science education but have also been identified as primary tools for achieving STEM integration (Kelley and Knowles, 2016; Hallström and Schönborn, 2019). As technological advances make computational models easier and more accessible, the ability to interpret these models is a driving factor for the integration of technology into other fields of science and engineering that, in turn, creates a need to include modeling as a component of STEM courses (Schwarz et al., 2009; Kelley and Knowles, 2016). To this end, numerous research studies have been conducted to understand and measure how students conceive of scientific models (e.g., Schwarz et al., 2009; Louca and Zacharia, 2012). The knowledge to understand and work with models, to create models within scientific practice, and to apply that knowledge to authentic context is often referred to as modeling competence (Upmeier Zu Belzen et al., 2019; Nielsen and Nielsen, 2021; Chiu and Lin, 2022). In a systematic review of empirical research on assessing modeling competence, Nicolaou and Constantinou (2014) found that modeling competence falls into two primary categories—namely, *modeling practice,* which is the ability to create and use models, and *meta knowledge of models* (also referred to as *metamodeling knowledge*), which is the understanding of the purpose, process, and use of models. This second category, meta knowledge of models, refers to the epistemological awareness about the nature and purposes of models and modeling, which is a form of metacognitive knowledge (e.g., Grosslight et al., 1991; Schwarz et al., 2009; Fortus et al., 2016; Upmeier Zu Belzen et al., 2019; Lazenby et al., 2020) rather than cognitive knowledge of the modeling process. In this project, students did not create their own models but instead engaged in activities that highlighted the utility of the modeling process to interpret simulated biological phenomenon. Thus, we use metamodeling knowledge as a measure of students' understanding of scientific modeling.

In a highly cited article based on their work on the Modeling Designs for Learning Science (MoDeLS) project, Schwarz et al. (2009) sought to develop a set of learning progressions for metamodeling knowledge. They identified three components of metamodeling knowledge: nature of models, purpose of models, and the criteria for evaluating and revising models. The *nature of models* component includes an understanding that models are an abstract rather than literal representation of real-world phenomenon and that different models have different advantages and limitations. *Purpose of models* includes an understanding that models are a tool to advance knowledge about the world and specific phenomena (e.g., for explanation or for prediction). Finally, there should be an understanding that models change based on information that is generated from accumulated empirical data. Thus, the component of *change* as an essential criterion for evaluating and revising models is an important aspect of metamodeling knowledge (Grosslight et al., 1991; Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019).

In comparing student metamodeling knowledge to that of experts, three levels of thinking about models have been identified (Grosslight et al., 1991; Upmeier Zu Belzen et al., 2019). In Level 1 thinking, models are viewed as exact replicas of reality and are assessed based on whether they "correctly" illustrate reality. In Level 2 thinking, models are understood to have a purpose that dictates the nature of the model. The model can be used to communicate something about the already known reality it represents, but the main focus is on the model itself rather than the underlying ideas. A Level 3 understanding identifies models as part of the scientific process from which data can be collected and analyzed. Gogolin and Krüger (2018) found that most high school students have a Level 2 understanding of the nature of models and a Level 1 understanding of the purpose of models, though with some variation across grade level and context. They noted that only a handful of students reached Level 3 understanding about the nature and purpose of models and theorized that this was due to a lack of emphasis on models as tools for hypothesis and prediction within classroom instruction. As models are becoming more ubiquitous in science classrooms and are an integral tool for learning about complex systems, there is a need for a more explicit focus on promoting understanding of scientific models across contexts at the high school level (Nicolaou and Constantinou, 2014; Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019; Lazenby et al., 2020).

2.3. Complex systems modeling

Scientific computational models such as agent-based simulations can help the process of developing systems thinking and an understanding of complexity by enabling students to dynamically observe the interactions and interdependencies of individual parts and emergent system-wide patterns as they develop over time (Chi, 2005; Jacobson et al., 2011; Markauskaite et al., 2020; Yoon et al., 2022). Several studies have been conducted on complex systems modeling using agent-based simulation tools such as NetLogo and StarLogo Nova (e.g., Hmelo-Silver et al., 2017; Yoon et al., 2017; Markauskaite et al., 2020). The use of the agent-based modeling simulation StarLogo Nova allows for three different representations of the complex system being modeled: first, a visual representation of the interactions of the complex system model; second, mathematical representations of specific outputs over time; and, finally, the blocks-based code representation used to build the model (see Figure 1). It has been shown that multiple representations of the same system can support students' understanding of the system (Jacobson et al., 2011; Ryu et al., 2015; Hmelo-Silver et al., 2017).

In our previous research, we have shown that the use of biological agent-based simulation in StarLogo Nova led to improvement in both biology and complex systems understanding (Yoon et al., 2017, 2020b). These findings are supported by the work of others, which showed that agent-based simulations of complex systems support the development of students' understanding of complexity (e.g., Jacobson et al., 2011; Hmelo-Silver et al., 2017). Hmelo-silver et al. (2017) found that the use of an agent-based computational model of an ecosystem led students to a deeper understanding of the causal mechanisms within a complex system compared to students in a control group who did not engage with models. However, a CMP framework for complex systems understanding only focuses on macro-level structural components and does not consider understanding of complexity from emergence. Additionally, the study measured modeling practice against complex systems knowledge, rather than focusing on metamodeling knowledge. Similarly, Markauskaite et al. (2020) examined modeling practices in connection with a specific complex system of climate change but focused more on the content knowledge connections than generalizable components of complex systems knowledge. This suggests there is space for more research into the explicit nature of the relationship between students' metamodeling knowledge and their knowledge of complex systems (Markauskaite et al., 2020) and how the affordances of the models support growth in understanding of complexity.

3. Methods

This is a mixed methods study that combines qualitative coding and analysis of open-ended responses with quantitative analysis of the coding in order to explore the relationship between students' knowledge of modeling and knowledge of complex systems.

3.1. Intervention details and study parameters

This study is part of a long-standing program of research that has sought to increase engagement with and understanding of biology systems through the design and dissemination of a curriculum to teach common topics in high school biology through agent-based complex systems models. The curriculum is built around the computational modeling tool StarLogo Nova. The curriculum includes five units, each of which utilize their own complex system model, and each of which focuses that model on a particular topic typically taught in high school biology: genetics, evolution, ecology, the human body, and animal systems. They entail working with the scientific models to engage in core scientific practices as outlined in the NGSS, such as analyzing and interpreting data, engaging in argument from evidence, and obtaining, evaluating, and communicating knowledge claims. The student and teacher materials for the units engage learners with the nature and purpose of models by asking students to make predictions about what will occur in the system and then having them change the model parameters to test and observe what happens. Figure 2 presents a page from the student activity packet for the human body model; students are asked to observe the model, predict what the model will do using different input conditions, and then run the model with different conditions and record what the model does. Students normally worked in groups of two to complete the units, each of which take 2 to 3 days to complete. The program of research has been published on extensively; see previously published work for more details on the context of the program (e.g., Yoon et al., 2019b; Yoon, 2022).

This study encompasses data collected during the 2019–2020 and 2020-2021school years. The project shifted from an in-person format for teacher recruitment and training to an online format in 2018; 2019 was the first year that the program was fully accessible online for teachers to participate in training. It is important to note that the Coronavirus pandemic began during spring of 2020 and, as a result, the context of classroom implementation shifted across the time period of this study, as many teachers switched from in-person to hybrid or fully remote learning.

3.2. Participants

One of the goals of the larger study was to understand the efficacy and effects of the curriculum across different contexts. As such, this study involved eight teachers from five different schools in two countries (U.S. and India). These teachers were chosen from the larger group of 42

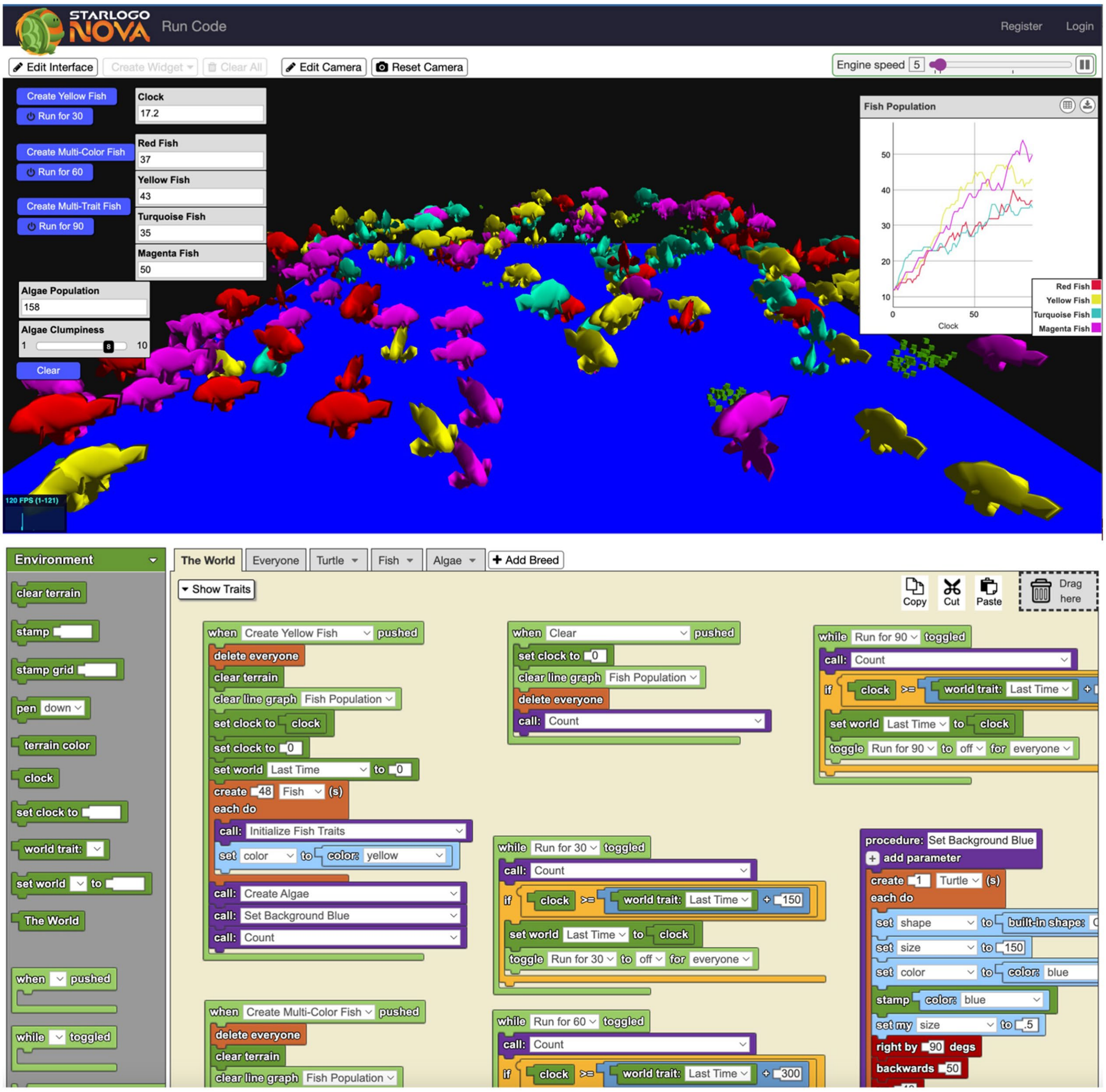

FIGURE 1
StarLogo Nova Interface: Model on Evolution. The top image shows the simulations of the fish interacting in the virtual environment. The mathematical representation can be seen in the top right in the form of a time-series graph, and the bottom half of the figure depicts the code used to build and run the simulation.

teachers who completed the online training course in 2019 based on several parameters, including their high level of engagement with the PD course, their commitment to implementing at least three of the five modules throughout the school year, their student populations and the degree of survey completion, and their interest in and enthusiasm for participating in the study. Ultimately the primary reason for selection was the teachers' agreement to participate in the research. The study encompasses 2 years of implementation. Three of the eight teachers implemented the curriculum in both years of the study. The teachers all identified as female, and their teaching experience ranged from 3 to 28 years in the classroom. A summary of the teachers' descriptive statistics can be found in Table 1. Each of the participating teachers implemented at least three of the units; therefore, the participating students worked with at least three different agent-based simulations of complex systems.

A total of 369 students participated in this study. Descriptive statistics for the student participants can be found in Table 2. Most of the teachers implemented the curriculum with ninth-grade students; however, a few of the classes were mixed grade and therefore included upper classmen.

3.3. Data sources

To investigate our research questions, survey tests of students' pre-and post-implementation complex systems knowledge and metamodeling knowledge were conducted in both years, and student focus group interviews were conducted in Year 2 to further probe the relationship between modeling and complex systems knowledge.

Experiment 1: The Conversion of Starch to Sugar WITHOUT ENZYMES

In Experiment 1, we'll observe the breakdown ***without enzymes*** of dissolved starch into sugar.

Follow your teacher's instructions to open up the Enzymes activity simulation file on your computer.

Click "Run Code" located at the top of your window on the black bar.

Click on the **Create 50 Starch** button and click **Run for 30.** This will populate the simulation with 50 starch molecules and the simulation will run for 30 computer seconds. Carefully observe what happens.

1) Describe what you see.

In our first experiment, we'll determine the relationship between the starting amount of dissolved starch (substrate) and the amount of sugar produced after 30 seconds *without enzymes*.

2) Predict: As you increase the starting amount of starch, what do you think will happen to the amount of sugar you end up with?

Experiment 1 Data Collection:

To determine the change in the amount of sugar produced as the amount of starting starch is increased, you will vary the amount of starch at setup and record the amount of sugar produced at 30 seconds.

FIGURE 2
Student Activity Packet: Enzymes in the Human Body.

TABLE 1 Teacher descriptive statistics.

Teacher	School	Country	Years of teaching experience*	Year implemented	# Students 2019–2020	# Students 2020–2021
1	A	India	28	2019–2020	7	
2	A	India	15	2019–2020	26	
3	B	India	20	2019–2020	10	
4	C	U.S.	7	2019–2020	14	
5	C	U.S.	13	2019–2020, 2020–2021	51	33
6	D	U.S.	8	2019–2020, 2020–2021	46	58
7	D	U.S.	5	2019–2020, 2020–2021	36	57
8	E	U.S.	3	2020–2021		31
Total					190	179

*At end of 2019–2020 school year.

Students completed two surveys pre-implementation and two surveys post-implementation. Though the surveys contained the same questions, they were administered 9 months apart, to mitigate the effects of item exposure. The first survey consisted of one open-ended question to measure their knowledge of complex systems (i.e., "Imagine a flock of geese arriving in a park in Philadelphia, where geese have not lived before. Describe how the addition of these geese to the park may affect the ecosystem over time. Consider both the living and nonliving parts of the ecosystem."). The second survey included three open-ended questions about scientific models. These were: (a) How would you describe what a scientific model is to someone who did not know what a model is?; (b) Describe what models are used for and how they could be used in science; and (c) What, if anything, would cause a scientist to change a model of a scientific concept? These three prompts about models were designed to solicit understanding of the three components of metamodeling knowledge (Schwarz et al., 2009).

In Year 2, which was taught mostly remotely or through hybrid remote and in-person learning, virtual semi structured focus group

TABLE 2 Student descriptive statistics.

Student characteristics	2019–2020 cohort	2020–2021 cohort
Number of students	190	179
Gender		
Male	84	75
Female	98	101
Nonbinary	0	1
Other	1	0
Grade		
8th	NA	1
9th	126	156
10th	33	7
11th	6	3
12th	20	11
Nationality		
United States	147	179
India	43	NA
Ethnicity		
White	74	97
Black	4	7
Asian & Pacific Islander	91	51
Hispanic	4	7
Multi-ethnic or other	9	14

Bold values are the combination of Years 1 and 2.

interviews were conducted over Zoom with one or two groups of three to five students from each class for a total of six focus group interviews across the four teachers participating in Year 2 implementation. These interviews sought to explore how students experienced the models in relation to their understanding of complex systems and conduct deeper exploration into the affordances those models and the process of modeling provided in order to more fully answer the third research question. Some example questions from these interviews include: Based on your understanding of biological systems, what characteristics do they exhibit, and *how* do you know this from the models? and What do you think are characteristics of good scientific models or explanations in terms of helping you learn or understand the science behind them? These interviews ranged in length from 52 to 66 min and were recorded and transcribed for analysis.

3.4. Data analysis

Analysis for this study was conducted using a mixed methods approach that combined qualitative and quantitative strategies for measuring student learning of scientific models and complex systems.

3.4.1. Coding of students' complex systems and metamodeling knowledge

Three separate rounds of qualitative analysis were conducted on the data for this study: coding of the open-ended responses on content knowledge for complex systems; coding of the open-ended responses on metamodeling knowledge; and mining of interview transcripts for information that supported the findings from the coding and quantitative analyses.

The coding manual used for coding the complex systems open responses has been reported on previously (see Yoon et al., 2016, 2020b). The coding manual was originally constructed from theories presented in Pavard and Dugdale (2000) and refined based on Jacobson et al. (2011) and through over a decade of use in studying complex systems understanding. The manual consists of four components each scored on the level of understanding as 1 (clockwork), 2 (emerging complexity), or 3 (complex) for a possible total score from 3 to 12. Table 3 presents descriptions of the components and example responses from students at the clockwork and complex levels of understanding. For example, the student response provided below is an example of a Level 3 (completely complex) understanding in the component of predictability because the student lists many different options for potential directions the ecosystem could take and uses the word "could" to show unpredictability:

> *Since the geese arrive at a place they haven't ever been before, there are many ways they can affect the ecosystem and it is impossible to say exactly how. For example, they could drive other birds away so that they can lay eggs. They could drive other birds away because they compete for the same kind of food. They could cause the increase of other animals who feed on geese. They could cause the increase of other birds because the geese have become an alternative food source for existing predators. It's really hard to tell.*

However, despite representing completely complex thinking for predictability, this response also depicts a Level 2 (emerging complexity) understanding for the other three components. For example, while acknowledging the existence of other species with agency in the ecosystem, the response is still centered on the geese as the central driving factor in the changes that occur in the system, which is scored as a Level 2 understanding in the category of order.

Responses to the complex systems survey were coded by three members of the research team in two rounds, one for each year of the study. As there were two responses that needed coding for each student (pre-and post-test), there were 380 responses from Year 1 and 358 responses from Year 2. One of the researchers was involved in coding responses from previous iterations of the project and conducted training on the codebook for the other two researchers. After multiple rounds of test coding, an inter-rater reliability test was conducted on 80 responses (21%), and a Cronbach alpha correlation coefficient of $\alpha = 0.863$ was achieved, which represents good reliability (Stemler and Tsai, 2008). After the disagreements were discussed and resolved, the remaining responses were divided evenly among the three researchers for coding. For Year 2 coding, the three researchers reconvened about 9 months later and conducted a second inter-rater reliability test on 72 of 358 responses (20%) from Year 2 and received a correlation coefficient of $\alpha = 0.858$. The disagreements were again discussed and resolved, with the remaining responses divided evenly among the three researchers for coding.

The coding manual for the modeling responses was adapted from prior work conducted on measuring metamodeling knowledge (Grosslight et al., 1991; Schwarz et al., 2009; Fortus et al., 2016; Gogolin and Krüger, 2018; Lazenby et al., 2020). Responses were scored on a scale of 1 (models as copies of reality) to 3 (models as tools for understanding and predicting reality) for each of three different

TABLE 3 Properties of complex systems knowledge.

Complex systems components	Descriptions	Level descriptions and example responses
Predictability	The emphasis is on the predictability of the effects caused by the agent in question. In a complex framework, it is impossible to precisely anticipate the behavior of the system. This is because the actions of agents cannot be predicted (as random forces or chance factors can affect an agent's actions) even if we know the rules or characteristics of the agent.	*Level 1: Clockwork – Agent actions/effects are predictable.* No alternative possibility is offered in the response. Certain words may hint at predictability of the effects of agents: "will," "is going to lead to/cause." Example: *When the geese are there, I think that it would greatly affect the people who go there. A lot of people would leave because of the bird poop.* *Level 2: Emerging Complexity – Agent actions/effects are largely predictable consider alternative possibilities.* The tone of the response indicates that agents' effects are somewhat predictable. However, some randomness in the system is suggested. More than 1 alternative is offered, or the answer has a minimum of two instances that indicate uncertainty in the outcome (e.g., the use of "probably" or "maybe"). Example: *If the geese arrive, they would probably help the ecosystem. The bird droppings might make the soil fertile [1st alternative]. It would start to look a lot greener. However, the increase of plants and roots might cause paths or walkways to be damaged [2nd alternative].* *Level 3: Complex – Agent actions/effects are unpredictable.* There are many alternative possibilities suggested in the response. Certain words discuss the unpredictability of the effects of agents: "may," "perhaps," "maybe," "evolve." Example*: Since the geese arrive at a place they have not ever been before, there are many ways they can affect the ecosystem and it is impossible to say exactly how. For example, they could drive other birds away so that they can lay eggs. They could drive other birds away because they compete for the same kind of food. They could cause the increase of other animals who feed on geese. They could cause the increase of other birds because the geese have become an alternative food source for existing predators. It's really hard to tell.*
Processes	The focus is the dynamism of the mechanisms that underlie the phenomena (i.e., how the system works or is thought to work). In a complex systems framework, there is no definite beginning and end to the activity. System processes are ongoing and dynamic.	*Level 1: Clockwork – Characterized by static and punctuated events* Response indicates that the system is composed of static events. While perturbations (actions by/on parts) in the system may cause change to occur, the change terminates once an outcome is achieved (i.e., there is a definite end). Example*: When geese arrive in the park, it would greatly affect the people who go there. A lot of people would leave because of the amount of bird poop. People would also leave because of all the birds flying around. The statues in the park would be corroded and fall off, which also cause people to leave.* *Level 2: Emerging Complexity – Somewhat static but recognizes that changes occur over a long period of time.* Response indicates that the system reflects some continual movement, fluctuations, and changes. There is indication of various components in the system increasing and decreasing. Responses that include a word or phrase that indicate a significant passage of time, such as "over time" or "eventually" would also warrant a level 2 code. Fundamentally however, there is an end. Example: *Geese may chase off other animals which could stop geese from eating the food they normally eat. These animals would have to adapt [dynamic – signals emerging complexity] or die. The other animals in the park will have to fight with the geese for food, and shelter. Once a species wins [suggests an end], the other types of animals may move away or die [possible end].* *Level 3: Complex – Continual state of activity and fluctuation to maintain balance* Response indicates that the system is an ongoing, dynamic process. Perturbations cause changes to the system, and the system continues to be in a state of flux (i.e., continual, and reoccurring changes happening to the system). The parts adapt or evolve and continue to do so accordingly. There is a sense that despite these changes, the system is maintained. Example: *The geese would eat some animals to survive. This may increase the competition for the same food with other animals. The other animals may leave the park to seek greener pastures. They and the geese may also simply starve, and their populations decrease. However, over time, with more geese in the park, the amount of nutrients in the soil is likely to increase as there is more decaying matter (feces and dead geese). This allows the park to support more producers and consumers. At the same time, overcrowding may occur. The lack of space may again decrease the populations.*

(Continued)

TABLE 3 (Continued)

Complex systems components	Descriptions	Level descriptions and example responses
Order	The focus is the organization of the system or phenomenon as centralized or decentralized. In a complex systems framework, control is decentralized and distributed to multiple parts or agents. Order in the system is self-organized or 'bottom-up' and emerges spontaneously.	*Level 1: Clockwork – Central agent has the power or force to impose order on the system* Response indicates that the system is perceived to be controlled by one central agent (i.e., all action is dictated by a leader). Order in the system is established 'top-down' or determined with a specific purpose in mind. Example*: Since the geese have not lived in the park, they probably do not know where to get food from. No goose from the population would be able to tell the rest [a central actor] so there is little effect of geese on the park ecosystem.* *Level 2: Emerging Complexity – Order of the system is distributed amongst several agents.* Response indicates that the system is largely perceived to be controlled by at least 2 agents but that these agents dictate how the system behaves. Thus, order in the system is still established 'top-down' with a specific purpose in mind. Example: *When the geese [a central actor] are there, it would affect the people who go there. A lot of people would leave because of the amount of bird poop, and the birds are constantly flying around. All the fountains and benches would be corroded by the bird poop, and since there are so much poop around, there would be more flies. The predators [a central actor] that usually hunt the geese would move to that area too.* *Level 3: Complex – Numerous agents* Response indicates that the system is decentralized (i.e., there is no central agent controlling the system). (Response indicates at least 3 agents.) Order in the system is self-organized or 'bottom-up' and emerges spontaneously. Example*: When geese come to the park, they will eat most of the grass. There will be a decrease in the food that geese eat. The caterpillars and the other grass-eaters will starve, die or move to another place. This means the decomposers will have less to eat, and probably decompose any dead geese faster. The soil may have less nutrients and the trees may grow less green.*
Emergence and scale	Emergence refers to the phenomenon where the complex entity manifests properties that exceed the summed traits and capacities of individual components. In other words, these complex patterns simply emerge from the simpler, interdependent interactions among the components. In a complex system, because parts or agents are interdependent in multiple ways, an action (small or large) that is imposed on the system may have large and far-reaching consequences on the numerous parts and agents of the system. This may in turn result in large-scale change and evolution.	*Level 1: Clockwork* Response indicates that (a) the parts of a system are considered to be isolated, where there is no interdependency among them; and (b) there is a sense that the action causes localized changes only. Example: *The geese are staying because they probably have a good resource of food here. The number of bugs will therefore decrease.* *Level 2: Emerging Complexity* Response indicates one complex component of emergence: either (i) a small action creates a large effect (scale) OR (ii) initial action has a cascading effect on several components of the ecological system that indicates interdependence, for example a change in the food chain (emergence) Example: *The geese arrival would drive the other birds away so they can lay eggs. There would be less worms that geese eats. People may see the geese and try to feed them. A lot of these things can fall into the lake and cause the fish to eat them and they may die. (Interdependency is evident between geese and worms, geese and fish, geese and other birds, etc.)* *Level 3: Complex* Response indicates that (a) the parts cannot be understood by decomposing them from the larger system because of their interdependency in multiple (2 or more) ways; and (b) there is a sense that the action can produce both localized changes and cascading effects (small actions → large effects). Example*: The geese will probably help the ecosystem. First, their droppings might make the soil more fertile, and plants will grow better. There may be more O2 as a result. The result of O2 and plant increase could cause a wet and warm ecosystem. However, geese may also eat most of the grass. Other grass-eaters will die or move. This would mean that the decomposers will have less to eat. The soil may have fewer nutrients, and the trees will grow less well. The geese may also damage statues with their droppings.*

dimensions of metamodeling knowledge (Schwarz et al., 2009). These dimensions are listed and explained in Table 4. The responses to three separate open-ended questions were combined into a single response for coding, and codes of 0 were allowed for responses that consisted of "I do not know" or blank answers for one of the dimensions. Therefore, total possible scores ranged from 0 to 9.

To explain the coding in a little more detail, below is a sample response from a student:

> *I would describe [a scientific model] as something that shows or represents in detail what the science is trying to show. Models are used to visualize things and to get a better look and understanding.*

TABLE 4 Properties of metamodeling knowledge (MMK).

MMK property	Description	Level descriptions and example responses
Nature	The "nature of models" property represents how a model is conceptualized. This includes how literal models are believed to be and how general or specific they can be.	*Level 1*: Models are literal replications of a single phenomenon that can be perceived by human senses. At this level, a model is believed to be "correct" or "wrong" based on its adherence to reality. Example: *"A model is a miniature replica of the original concept aiming to provide a better understanding about the concept. It is a detailed visual representation."* *Level 2:* Models are idealized representations of a phenomenon that may not be accessible to the human senses. Though models might not be literal replications of reality, they are based entirely on existing data from reality. At this level, models are understood to be created by a modeler with a purpose that dictates certain choices about how the model represents reality. Example: *"A scientific model is a model used to describe a scientific process of concepts. It can either be either physical or virtual but in some way, it will model either the concept of the process that it was supposed to represent."* *Level 3:* Models are a reconstruction of a phenomena (or a series of related phenomena), based on theoretical understanding, data, and hypothesis. Importantly, at this level there is an understanding that models can extend beyond rigid adherence to existing data and can include hypothetical theories. At this level, models are known to represent multiple interrelated systems or phenomena. Example: *"A scientific model is a creative representation or formulation of an idea that is created in order to analyze how that idea would fit into the real-world using evidence and scientific knowledge."*
Purpose	The "purpose of models" property represents the reason for a model's existence and what can be achieved with it. This includes the way it is used to communicate and to conduct predictions or discover new information and understanding.	*Level 1:* Models are used to demonstrate how something looks or operates on a superficial level. Their purpose is to describe only. Example: "*Models are used to visually show about the real thing*." *Level 2:* Models are used to explicitly highlight underlying mechanisms or key concepts within a phenomenon. This differs from Level 1, where representations aim for superficial replication and direct representation of the overall phenomenon. At Level 2, models have been shifted from direct visual replications of reality to communicate something specific about how the phenomenon functions. Example: "*It is a representation of a concept or system of ideas used to provide further explanation or clarification. Models are used for organizing ideas and explanations to understand systems or complex ideas in science. They could be used by a presenter or scientist explaining ideas to another, or to simply record discoveries.*" *Level 3*: Models are used to interpret or predict the process or outcome of a phenomenon or system. The purpose of models is to serve as a thinking aid to guide the construction and interpretation of data. Models can lead to new understandings and hypotheses. Example: "*Scientists use models to identify patterns in the world. Based on their knowledge with these models and scientific knowledge they can make predictions on future patterns.*"
Change	The "changeability of models" property demonstrates how and when a model could or should be changed and the reason or purpose for doing so.	*Level 1:* Models may be changed if there is something wrong with them, if errors are found, or if the model is not communicating effectively. There is one "correct" model. Example: *"If their model was incorrect or not used properly."* *Level 2:* Models may be changed if new data or information is discovered about the underlying phenomenon. At Level 2, responses may be referring to the process of aligning the model with more modern or contemporary understandings of the underlying science. Example: *"If new information comes out disproving the previous scientific model."* *Level 3:* Models are revised as part of a cyclic process of prediction, data collection, and analysis. The interpretation of data from the model is the agent of change. Example: *"Based on their new findings and new concepts that they are developing in their experiment."*

> *[A scientist might change a model if] they saw that their model didn't accurately represent the data they're trying to show.*

In this response, the use of the words "show" and "accuracy" demonstrates an understanding of a model as a static representation of an intended outcome whose role is to depict that outcome in alignment with expected reality. This response was scored as a Level 1 for all three properties. In contrast, the following example response demonstrates a more advanced level of metamodeling knowledge:

> *A scientific model is a concept to make something easier to understand. It could be any type of model to visualize something that is being experimented. Models are used to represent something in the real world. It is a way that scientists can make predictions and propose new ideas. [A scientist might change a model] based on their new findings and concepts that they are developing in their experiment.*

In this second response, the student recognizes the active role of models in the scientific process (scored as a 3 for purpose) and cycle of changing models as part of that process (scored as a 3 for change). While they still connect models to real-world representations, they understand that a model is not an exact replica (scored as a 2 for nature of the model).

We worked with a member of the research team who was not involved in creating the codebook to test the coding manual for understanding and clarity. Two additional researchers were trained on the codebook who achieved an inter-rater reliability Cronbach alpha coefficient of $\alpha = 0.90$ on 70 responses (9% of the total of 738 over the 2 years). We realize that this is less than the standard of 20% of the data used to obtain interrater reliability, there were additional time constraints and availability of the coders decreased substantially due to the time of year that coding was requested. However, as the alpha coefficient is well over the 0.70 limit indicating good reliability (Stemler and Tsai, 2008), and as the sample is large, we deemed this was a sufficient measure of reliability and decided to proceed with coding of the remaining responses. After the differences were discussed, one researcher (first author) coded the remaining responses.

The student focus group interviews were mined by the first author for responses that could explain how the curriculum and models afforded better understanding of complex systems. Responses were then grouped into themes that supported the three categories of metamodeling knowledge.

3.4.2. Relationship between students' complex systems and metamodeling knowledge

The resulting codes were compared pre-to post-test scores for both modeling knowledge and complex systems understanding. A paired samples t-test was conducted to determine whether there was positive significant growth in both measures. The results were then analyzed to understand whether there was a relationship between the two measures through hierarchical regression modeling. The analysis was conducted to determine whether there was a significant effect on complex system understanding beyond their prior knowledge of modeling and understanding of complex systems measured at the pre-test survey.

4. Findings

Results from the analysis of the coded open-ended survey responses revealed significant growth in both metamodeling and complex systems knowledge. The results of the regressions analysis showed that modeling knowledge had a significant positive effect on complex systems understanding when holding all other variables constant. Finally, the student focus group interviews supported these findings with quotes from students depicting how aspects of the models were viewed to enhance their learning of the complex biological systems.

4.1. Knowledge growth in both scientific modeling and complex systems

The results of the surveys showed growth from pre-test to post-test for both measures, where a paired samples t-test showed positive significant growth t (368) = 6.03, $p < 0.001$ with a Cohen's d effect size of 0.39 for students' modeling knowledge which is a small to medium effect (Lakens, 2013), and positive significant growth t (368) = 4.62, $p < 0.001$ with a Cohen's d effect size of 0.27 which is a small effect for students' complex systems understanding (see Table 5 for more details).

While these results supported previous findings that students experienced growth in their complex systems knowledge, in this study we were primarily interested in the relationship between change in modeling knowledge and complex systems knowledge. This relationship was explored through a regression analyses.

4.2. Change in metamodeling knowledge has significant positive impact on change in complex system understanding

To test if students' metamodeling knowledge improved their understanding of complex systems beyond their prior knowledge of modeling and understanding of complex system measured at the pre-test, a hierarchical regression was conducted with two blocks of variables. The first block included students' pre-test of knowledge of modeling and pre-test of knowledge of complex system as the predictors, and with students' post-test measure of understanding of complex system as the dependent variable. In block two, students' post-test measure of metamodeling knowledge was also included as the predictor variable, with students' post-test measure of understanding of complex system as the dependent variable (see Table 6 for a summary).

Overall, the results show that the first model was significant F (2,366) = 28.85, $p < 0.001$, $R^2 = 0.14$. But only students' pre-test measure of understanding of complex system was significantly associated with the post-test measure of understanding of complex system ($b = 0.37$, $t = 6.81$, $p < 0.001$). The second model (F (1,365) = 32.49, $p < 0.001$, $R^2 = 0.21$), which included students' post-test measure of modeling knowledge ($b = 0.33$, t = 5.70, $p < 0.001$), showed significant improvement from the first model, $\Delta R^2 = 0.07$, $p < 0.001$. Overall, when students' pre-test of knowledge of modeling and pre-test measure of understanding of complex system were included in the model, the variables explained 14% of the variance. The final model, including students' post-test measure of understanding of modeling, accounted for 21% of the variance. Thus, with the addition of the second independent variable of students' post-test modeling scores, results showed that it significantly predicted students' complex systems understanding in the post-test beyond students' prior knowledge of modeling and understanding of complex systems measured at the pre-test.

TABLE 5 Scientific metamodeling and complex systems knowledge.

		Scientific metamodeling knowledge			Complex systems knowledge		
Year	N	Pre-test avg (SD)	Post-test avg (SD)	Diff	Pre-test avg (SD)	Post-test avg (SD)	Diff
Year 1	190	4.47 (1.51)	5.31 (1.33)	0.84	5.97 (1.46)	6.28 (1.56)	0.31
Year 2	179	4.79 (1.41)	5.05 (1.35)	0.26	6.04 (1.51)	6.58 (1.63)	0.54
Both Years	**369**	**4.63 (1.47)**	**5.18 (1.34)**	**0.56**	**6.01 (1.48)**	**6.43 (1.60)**	**0.42**

Bold values are the combination of Years 1 and 2.

TABLE 6 Results of regression of post measure of understanding on predictors.

Predictor	Variables	B	*t*	Sig.
Model 1				
	Pre-test of understanding of complex system	0.37	6.81	< 0.001
	Pre-test of modeling	0.83	1.52	= 0.130
Model 2				
	Pre-test of understanding of complex system	0.34	6.46	< 0.001
	Pre-test of modeling	0.03	0.52	= 0.602
	Post-test of modeling	0.33	5.70	<0.001

$R^2 = 0.14$ for Model 1, $p < 0.001$; $\Delta R^2 = 0.07$ for Model 2, $p < 0.001$; Total $R^2 = 0.21$, $p < 0.001$.

4.3. How metamodeling knowledge supports complex systems learning

To answer our third research question about the specific affordances that allowed for the connection between metamodeling knowledge and complex systems understanding, an analysis of the student focus group interviews was conducted. The three components of metamodeling knowledge: nature of models, purpose of models, and the criteria for evaluating and revising models (Schwarz et al., 2009) were identified within the interviews and three themes emerged that connect those components of metamodeling knowledge to complex systems understanding and highlight specific affordances of the StarLogo Nova models that support students' complex systems understanding development. For the nature of models, students focused on the "realistic" quality of the models, which allowed for aspects of complex systems in biology to be viewed and explored. Students understood the purpose of the models to have a role in communicating different aspects of the system through the different representations within the model. Finally, students engaged with the changeability of models through manipulating parameters to highlight characteristics of complex systems such as randomness and interconnectedness.

4.3.1. The nature of models as "realistic" representations of complex systems

While viewing scientific models as exact copies of reality supports a low-level understanding of the nature and purpose of models, it is important to understand that models are used to represent reality in some way that is useful. The connection to reality was a component of the models that students were drawn to, and which was brought up by multiple students in response to a question about the nature of good scientific models. For example, a student from a focus group for Teacher 5 said, "They model a real-life system, so we can see how, in real life, they work. We can actually see each component of every system, and that really helped me, at least, understand how all these things work." In response to the same prompt, a student from Teacher 8's class identified the importance of keeping models close to reality while also modifying them to make them simple:

> *I generally think of things that are easy to navigate, but also keeping it realistic. So, they're not so simple that it's not enough information, but just the right amount that it still looks relatively real to what you're learning about. Keeping it simple but realistic at the same time, because if it's not realistic, it's not benefiting you for learning what that system really looks like.*

These quotes support students' metamodeling knowledge of the nature of models as *useful* representations of reality. Students also connected the realistic nature of the models to characteristics of complex systems. One student from Teacher 8's class said, for example, that "Even if you would test [the model] again and again, it was super unlikely you'd come to the same answer twice just because they are trying to make it as realistic as possible." A student from Teacher 5's class had a similar observation, saying "Getting different outcomes with different numbers or even that the same numbers, just like a more realistic model, and I think that's how scientific models should be." These quotes show that students were making connections between the nature of models and the nature of complex systems.

4.3.2. The purpose of models: to communicate through different representations of the system

Most of the students interviewed spoke about the purpose of models to communicate and explain complex systems through multiple representations of the system and the data within it. While the students did not talk about the code representation, both the visual and mathematical representations were highlighted as important factors in building their understanding of the complex systems and underlying concepts. A student from a focus group for Teacher 8 mentioned that having the visual representation was an added benefit over auditory methods she was more used to encountering, saying:

> *I feel like it really helped just to put a visual to the things that we were learning. Not just have the words in an auditory explanation of what was going on, but to see what was actually going on and have a good visual of it.*

Mathematical representations, in the form of graphs that tracked output data from the simulations, were also a source of information that students used to interpret complex systems. In the focus group with students from Teacher 5, one student responded to a comment about tracking changes in the system by highlighting the graphs, saying, "We could usually tell that by the two graphs on the side, which would kind of help to see how dramatic or undramatic the changes were."

Students also made connections between the visual and mathematical representations within the simulations. One student from a focus group for Teacher 6 talked about how the visual representation helped simplify the complexity while the mathematical representation helped him understand the process:

> *These models, they help simplify a very complex scientific idea and it helps me visualize and, for example, the graph for the gene*

> *regulation, it helps you understand how the graph was developed and instead of making biology feeling like it's something that's just needs to be memorized, it helps you understand the process more.*

The students recognized that having multiple representations of the model in the StarLogo Nova simulation allowed them to explore complex systems in multiple ways that helped them understand the concepts and complex systems in general. For these students, the model was a tool for building understanding.

4.3.3. Changing the model parameters to explore randomness and connectivity as components of complex systems

Though the students did not change the underlying code of the simulations, they did change the parameters that were used as initial conditions for running the model and chose different scenarios to model, which served as examples for thinking about model changeability. This ability to change the model in response to the data produced by the model in order to further explore the system being simulated supported students in developing complex systems knowledge. A student from Teacher 6's class explained this process:

> *Something else I noticed with this simulation was that you could customize the different scenarios, so that it fit with what you were trying to learn. I remember we would put in different barriers in different types of sugar. I remember that was really helpful because we could, and with all of the simulations too, you could create these different scenarios to separately explore different concepts.*

The changeability of the models allowed students to observe the connected nature of the complex systems and the way that the models were able to make those connections observable to them. In talking about the ecology model, one student in Teacher 5's class said,

> *What we learned was how when one species is affected, it's not just affected individually. It's kind of like a domino effect that affects the organisms it feeds on and the organisms that feed on it, which was really interesting.*

A student from Teacher 6's class made an explicit connection between this interconnectedness of the components of the models and the fact of that as a defining characteristic of complex systems saying,

> *There are a lot of different parts to all of [the models], it's just part of what a complex system is, and they all work together, and there are different outcomes based on how they work together, so I would say that's the characteristic that they exhibit.*

The students also noticed the ability of the models to simulate the emergent nature of complex systems, which can seem like randomness due to the complexity of the interactions of the components within the system. One student from Teacher 5's class noted the relationship between the randomness displayed by the models and what might happen in real life, saying,

> *One thing I noticed about these [models] is that the outcomes were kind of different every time. If multiple people in the class did the same numbers or same data, it wasn't guaranteed to get the same response and the same outcome. Obviously, that's how it is in real life.*

A student in Teacher 6's class made a connection between the randomness displayed by all the models and the unpredictability of complex systems, showing a high-level understanding of both the nature of models and of complex systems, saying, "All the models had different models of different parts of things, and they all moved randomly, and you have that element of unpredictability, which would be a characteristic of complex systems." Finally, a student from Teacher 7's class summed up all three of the themes from the interviews in a single quote, saying,

> *The graph there in the Gene Regulation, that's useful. So, it's not just that I think there's more of these over time and then they decrease, you can see the graph, you can see it's actually happening. Also, I think the randomness … In all of these, if you run the simulation multiple times, it's not just the same exact thing. The factors are working off each other with a bit of randomness. You can tell that whatever is happening is actually happening. In the real world, it's not going to be the same every single time. It's more realistic.*

These three themes and the quotes that illustrate them add further support to the quantitative analysis of the student knowledge surveys and suggest that there is a significant connection between students' metamodeling knowledge and their learning about complex systems. Students' ability to see models as useful representations of an aspect of reality and to understand that they could be manipulated to view that reality from different angles and different starting scenarios allowed them to develop a deeper understanding of complex systems and their emergent nature.

5. Discussion

Our findings answer our research questions in the following ways. There was significant growth both in students' metamodeling knowledge and in their complex systems understanding across both years of the study. The hierarchical regression analysis also showed a significant effect of students' growth in metamodeling knowledge on their growth in complex systems understanding. Furthermore, student interviews identified three distinct ways that their modeling experiences supported learning about complex systems, highlighting supports for metamodeling knowledge reported in the literature review (i.e., the nature, purpose, and changeability of models; Schwarz et al., 2009). From the focus interview responses about the *nature of models*, the agent-based simulations in our study enabled students to observe system structures through visualizations of system component interactions (Chi, 2005; Jacobson et al., 2011; Markauskaite et al., 2020). These dynamics are normally hidden to the naked eye, which makes it challenging to understand how system patterns emerge (Yoon et al., 2018a). Emergent patterns in biology, such as climate change or natural selection, are also difficult to witness in real time because they appear over large geographic and temporal scales (Grotzer and Tutwiler, 2014). Many students in our study noted that being able to see the system all at once was important to their learning. Regarding the *purpose of models*, the existence of multiple representations of the scientific phenomenon under investigation provided students with strategies to interpret data generated from multiple runs and to develop explanations of the system (Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019). Finally, regarding the *changeability of models*, the ability to manipulate initial conditions and the ability to compare varying results allowed students to develop more sophisticated scientific theories (e.g., that there is built-in variation and randomness in all systems) than what only a single run of the simulation would otherwise afford. These findings support previous research showing the affordances of computational models as tools for increasing students' complex systems understanding (e.g., Hmelo-Silver et al., 2017; Yoon et al., 2017; Markauskaite et al., 2020; Nguyen and Santagata, 2021).

While these findings support previous research and add to the research on modeling and complex systems by explicitly demonstrating a quantitative significant effect of metamodeling knowledge on complex systems understanding, there are limitations to the study. The sample of teachers in the study were self-selecting into the professional development for the StarLogo Nova simulations and resources, and into the study. As such, the teachers were highly motivated and likely represented an ideal population of students. Additionally, the Covid-19 pandemic made working with the teachers and students in India impossible for the second year of the study which limited the diversity of the students in the study and may have skewed the regression model. Another limitation is that, while this study focused on students' metamodeling knowledge, modeling practices were not measured and certain components of modeling competence such as *multiple models* and *testing models* (Upmeier Zu Belzen et al., 2019) were not included in the study. Finally, we acknowledge that this work is embedded firmly within the context of Biology and while metamodeling knowledge is conceived as content general knowledge, it has been found that there exists a difference between contextualized and decontextualized metamodeling knowledge so our results may only speak to contextualized knowledge (Göhner et al., 2022).

While acknowledging some limitations, the findings reported here emerge from over a decade of research on this project that involved years of iterative design and implementation cycles to reach a point where the curriculum and PD experiences fully supported teachers and students in using models to support learning of complex systems (see Yoon et al., 2016, 2020b; Yoon, 2022). Our research has produced significant outcomes for student learning and supported attempts to scale up access to project resources more globally (Yoon et al., 2020b). Developing greater understanding of complex systems (Yoon et al., 2018a) and systems more generally (NGSS Lead States, 2013) has also been a focus of educators and educational researchers for many years. Despite this longstanding interest, however, complex systems curricula and tools have still not made their way widely into biology classrooms (Gilissen et al., 2020; Markauskaite et al., 2020). Perhaps this slow progress is related to the lack of studies that make explicit the connection between growth in student understanding of complex systems and specific instructional approaches such as agent-based modeling, as noted in a previous literature review (Yoon et al., 2018a). Without assurances that learning outcomes will improve, it may be difficult to convince teachers to adopt new pedagogies and tools like ours that add additional time to the standard biology curriculum. That we found improvements in both student measures of metamodeling knowledge and complex systems understanding even in Year 2 of the project—where teaching and learning happened fully online—is also worth highlighting given the documented learning losses that we have experienced due to the pandemic (Nowicki, 2022).

6. Conclusion

In this study, we investigated how students' understanding of biological models using an agent-based modeling tool influenced their understanding of complex systems. Through many years of design iterations, we developed a curriculum that supports growth in students' knowledge of scientific models and complex systems understanding in high school biology. Through a regression analysis of 2 years of student data, we demonstrated that growth in students' modeling knowledge significantly predicted growth in their understanding of complex systems. We further showed that students perceived multiple aspects of the agent-based modeling tool as important to supporting their understanding of complex systems. Studies that demonstrate explicit relationships between instructional approaches and improvements in complex systems content learning are rare, which underscores the overall value and contribution of this research. We hope that future research will continue to explore the relationship between metamodeling knowledge and complex systems understanding both to replicate our work with different systems' representations to show that the effects are significant in other contexts and content areas, and to expand upon our work to include more components of modeling competencies (Schwarz et al., 2009; Fortus et al., 2016; Upmeier Zu Belzen et al., 2019). Specifically, embedding agent-based simulations within the scientific inquiry process to support students' deeper exploration of complex systems and their development of systems thinking.

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 University of Pennsylvania IRB. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

KM and SY contributed to conception and design of the study. KM performed the analysis and wrote the first draft of the manuscript. SY wrote sections of the manuscript. All authors contributed to the article and approved the submitted version.

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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

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EDITED BY
Moritz Krell,
University of Kiel, Germany

REVIEWED BY
Elon Langbeheim,
Ben-Gurion University of the Negev, Israel
Anna Beniermann,
Humboldt University of Berlin, Germany

*CORRESPONDENCE
Annika Lankers
✉ annika.lankers@uni-due.de

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Students' systems thinking while modeling a dynamic ecological system

Annika Lankers*, Justin Timm and Philipp Schmiemann

Biology Education Research and Learning Lab, University of Duisburg-Essen, Essen, Germany

The world is facing global ecological changes, making it essential to prepare the future generation with the necessary understanding to effectively navigate and address complex tasks. Previous research has shown that both systems thinking and scientific modeling are particularly relevant in investigating the comprehensive understanding of such complex phenomena. However, there has been little research on the interrelation between systems thinking and scientific modeling. To address this research gap, we conducted a thinking-aloud study with nine high school students by confronting them with a simulation of a dynamic ecological system. Our qualitative content analysis of the students' statements indicates an interrelation between systems thinking and scientific modeling. The students infrequently show systems thinking during the exploration, whereas when developing a graphical model, the students are involved in identifying the system organization and analyzing the system behavior. When predicting future system states, students engage in modeling the system evolution. Furthermore, during verbalizing analogies and experiences, students refer to the system organization and behavior, whereas in mental modeling, students additionally model the system evolution. These results illustrate a central difference between the two perspectives. Thus, scientific modeling focuses on students' activities during their understanding process, while systems thinking addresses students' analysis of systems and their properties. While the phenomenon exploration may not require systems thinking, pattern recognition and model development are frequently associated with identifying the system organization and analyzing the system behavior. Systems thinking must also be applied when deriving possible future system states by modeling the system evolution, an activity that is closely related to the prediction phase of scientific modeling. Interestingly, in our study, the students also demonstrated the modeling of system evolution in their mental modeling. In conclusion, a complementary consideration of systems thinking and scientific modeling affords a deeper understanding of students' cognitive processes in dealing with complex phenomena.

KEYWORDS

complex phenomena, systems thinking, scientific modeling, dynamic ecological system, alien species, science education, secondary students, qualitative content analysis

1. Introduction

Attention to global changes and its consequences have increased immensely over the last decades. The world is facing global social and environmental issues. One of them is biotic homogenization including several losing and a few winning species (McKinney and Lockwood, 1999). Of particular concern are invasive alien species, as they are a significant threat not only to biodiversity (Early et al., 2016). Invasions negatively affect ecosystem stability and have a direct impact on habitat design, ecosystem performance, agricultural success, the spread of diseases, and human well-being (IPBES, 2019). To deal with such global challenges, a comprehensive understanding of biodiversity and ecosystem functioning is critical for constructive policy and management (Early et al., 2016). Future generations must be prepared for these tasks by developing a holistic understanding of global changes facing the world community (NGSS Lead States, 2013; Ladrera et al., 2020). This issue persists, as the findings of the Programme for International Student Assessment (PISA) reveal that students with little knowledge and skills have naïve and unrealistic ideas about the self-regulation of the world, whereas scientifically educated students are able to make realistic assessments based on ethical reasoning (OECD, 2022). Hence, science education aims to provide students with a set of essential skills and subject-specific concepts that can be used as a basis for dealing with decision-making and problem solving in issues of global concern as well as everyday life challenges (National Research Council, 2012; NGSS Lead States, 2013). Systems thinking and scientific modeling are cognitive activities discussed in the context of a deeper understanding of such complex phenomena in dealing with personal, social, and global challenges (Jackson et al., 1991; Hogan, 2000; Gotwals and Songer, 2010; NGSS Lead States, 2013; Bielik et al., 2021). Both are directly related to understanding complex phenomena, but from different perspectives: Scientific modeling focuses on the process of accessing complex phenomena and primarily addresses how students proceed, whereas systems thinking primarily addresses how students analyze complex systems. Even though it seems plausible that there might be a close relationship between systems thinking and scientific modeling, the connection between the two perspectives has not yet been investigated systematically. This study investigates how students integrate systems thinking and scientific modeling when instructed to develop a model that explains the observed population dynamics of an ecological system invaded by an alien species.

1.1. Systems thinking

Systems thinking is a cognitive skill that provides the theoretical concepts for explaining and predicting natural phenomena (Verhoeff et al., 2018). In recent years, systems thinking has been examined for a variety of systems in manifold contexts, such as ecology (Riess and Mischo, 2010; Eliam and Reisfeld, 2017; Dor-Haim et al., 2022), human physiology (Liu and Hmelo-Silver, 2009; Tripto et al., 2018; Kiesewetter and Schmiemann, 2022), cell biology (Verhoeff et al., 2008), and biogeochemistry (Ben Zvi Assaraf and Orion, 2005; Lee et al., 2019; Torkar and Korfiatis, 2022). All (biological) systems share universal characteristics. For example, systems are composed of system elements that together form a complex whole. Ecosystems encompass the entirety of abiotic and biotic factors within a specific habitat. Despite their interconnectedness, (eco-)systems are open to their environment, allowing for the exchange of matter, energy, and information. Generally, the openness of systems is closely related to the dynamics of systems. Systems with constant composition of elements may exhibit temporary behavioral stability. However, over the long term, system dynamics can be significantly affected by internal factors or external disturbances, such as the presence of alien species as a destabilizing element (Andrade et al., 2015; Mehren et al., 2018). Understanding the complexity of system dynamics can be challenging (Wellmanns and Schmiemann, 2022). This especially applies to ecological systems undergoing degradation, which results in significant modifications to the ecosystem, leading to noticeable changes in species composition and overall dynamics (Zimmerman and Cuddington, 2007).

Several frameworks of systems thinking exist alongside each other (Ben Zvi Assaraf and Orion, 2005, 2010; Hmelo-Silver et al., 2007; Verhoeff et al., 2008; Riess and Mischo, 2010; Sommer and Lücken, 2010; Boersma et al., 2011; Hokayem and Gotwals, 2016; Hmelo-Silver et al., 2017; Snapir et al., 2017; Mehren et al., 2018; Gilissen et al., 2020; Mambrey et al., 2020; Momsen et al., 2022). However, many of these frameworks incorporate similar cognitive skills, even if individual frameworks assume different relationships between these skills or define additional skills (e.g., Ben Zvi Assaraf and Orion, 2005; Mehren et al., 2018). Most systems thinking frameworks consider in some way the following three skills: identifying the system organization, analyzing the system behavior, and modeling the system evolution. The first skill, identifying the system organization, covers recognizing the structure and boundaries of the system as well as identifying the elements and their relationships (Ben Zvi Assaraf and Orion, 2005; Evagorou et al., 2009; Riess and Mischo, 2010; Sommer and Lücken, 2010; Hmelo-Silver et al., 2015; Mehren et al., 2018; Mambrey et al., 2020). The second skill includes analyzing the system behavior by capturing system interactions and dynamics as well as emerging patterns (Ben Zvi Assaraf and Orion, 2005; Hmelo-Silver et al., 2007; Sommer and Lücken, 2010; Mehren et al., 2018; Mambrey et al., 2020). The third skill incorporates modeling the system evolution and thus the development of predictions (Ben Zvi Assaraf and Orion, 2005; Mambrey et al., 2020), possibly to derive regulatory measures (Riess and Mischo, 2010; Mehren et al., 2018). Overall, the naming of the individual skills is consistent with the terminology of Mambrey et al. (2020), who conducted research in the field of ecology, and thus based on the work of Mehren et al. (2018), who originally derived the three listed skills theoretically and empirically tested their model in the context of geography.

In addition to describing individual skills that constitute systems thinking, it is possible and reasonable to consider the complexity of systems thinking (Hokayem and Gotwals, 2016; Lee et al., 2019). Systems can be big or small, and relationships and behaviors may be simple or complex. Notably, there is a considerable difference between the degree of linkage in relationships (Jin et al., 2019; Mambrey et al., 2020, 2022b). Simple relations immediately connect two elements. Whereas relationships that involve a minimum of three elements form either a linear chain or a complex linkage through a central node. This can be well exemplified with a food web and the representation thereof. A statement mentioning rabbits eating grass would name a simple relationship (Mambrey et al., 2022b). This direct predator–prey relationship would be graphically represented by an arrow from prey to predator within a food web. In addition, a typical linear linked relationship is a food chain between a carnivore and a producer. The populations of grass, rabbit, and predator form a food chain as the elements are linked by two arrows in an unbranched manner. In contrast, we define all relationships as complex linked that do not represent mere chains but contain at least one branch (Mambrey et al., 2022a). The most simple example of a complex relationship is food competition between two herbivores such as rabbit and goose for grass, as the system is branched starting from the grass as central node. Previous research in the context of ecology shows that students often prefer to refer to low linked relationships including a small number of elements as an increased number of elements in a system strongly affects the difficulty of comprehension (Strogatz, 2001; Gotwals and Songer, 2010; Hokayem, 2016; Mehren et al., 2018; Mambrey et al., 2022b).

1.2. Modeling in systems thinking research

Various authors imply that systems thinking is connected in some way with models or modeling (Ben Zvi Assaraf and Knippels, 2022; Bielik et al., 2023). However, very different aspects of modeling have been emphasized in the systems thinking literature: Various frameworks explicitly include modeling as a systems thinking skill, which, however, can describe different skills. For example, modeling can involve inferring statements about future system states but also understanding and/or creating system models (e.g., Sommer and Lücken, 2010; Mehren et al., 2018; Gilissen et al., 2020; Mambrey et al., 2020; Streiling et al., 2021). From a different perspective, models are viewed as representations of complex systems (Streiling et al., 2021; Kiesewetter and Schmiemann, 2022; Mambrey et al., 2022b). In addition, they are the starting point for developing predictions (Gilissen et al., 2020). External representations of students' mental models are evaluated as expressions of their systems thinking and thus serve as an indicator of skill (Ben Zvi Assaraf and Orion, 2005; Brandstädter et al., 2012; Tripto et al., 2013). From yet another perspective, modeling can be used as an activity and strategy to improve systems thinking (Verhoeff et al., 2008; Wilson et al., 2020). Modeling thus can have a variety of meanings in the context of systems thinking; in this study we focus on the cognitive activity of scientific modeling.

1.3. Scientific modeling

Scientific modeling is a practice aimed at examining and explaining complex phenomena or systems (NGSS Lead States, 2013; Krell et al., 2019; Schwarz et al., 2022). It describes the process of gaining access to phenomena that are not completely accessible without further examination (Krell et al., 2019). Accordingly, the emerging models are not just products but useful tools for investigating phenomena (Gouvea and Passmore, 2017). The process of scientific modeling entails activities of model development, evaluation, and revision (Schwarz and White, 2005), which can occur individually or continuously and in cycles (Oh and Oh, 2011; Campbell et al., 2013; Gilbert and Justi, 2016; Krell et al., 2019). The frameworks of Clement (1989), Krell and Krüger (2016) and Justi and Gilbert (2002) provide a process-oriented conceptualization of modeling activities. Usually, the process of scientific modeling starts with the perception of a real-world phenomenon (Krell et al., 2019), based on which and with the activation of analogies and experiences, a mental model arises (Upmeier zu Belzen et al., 2019), which may be labeled mental (Nersessian, 2008), initial (Clement, 1989), or proto-model (Gilbert and Justi, 2016). The mental model is expressed or externalized in any kind of representation (Justi and Gilbert, 2002; Gilbert and Justi, 2016; Upmeier zu Belzen et al., 2019), which is subsequently evaluated for consistency (Clement, 1989; Krell et al., 2019). Once this evaluation is completed, an epistemological change of perspective may take place: A shift toward the epistemic usage of the model can be accomplished by working beyond the developmental perspective of scientific modeling (Gouvea and Passmore, 2017). This perspective of model utilization is characterized by the performance of empirical tests of model-based predictions (Clement, 1989; Justi and Gilbert, 2002; Giere et al., 2006; Gilbert and Justi, 2016; Krell et al., 2019; Upmeier zu Belzen et al., 2019). Therefore, comparing obtained data and predictions provides information on model fit (Krell et al., 2019). If the predictions turn out to be true, the model has proven its validity, at least within the scope of the predictions, and can fulfill its epistemic aim (Justi and Gilbert, 2002; Gouvea and Passmore, 2017; Krell et al., 2019). If the data do not bear out the prediction, the model needs to be revised or rejected (Clement, 1989; Justi and Gilbert, 2002). This leads back to the process of model development, thereby revealing the cyclic nature of scientific modeling (Schwarz and White, 2005; Oh and Oh, 2011; Krell et al., 2019). However, recent research has demonstrated that this cyclic nature of scientific modeling does not necessarily describe students' real procedures, as they tend to omit or jump between phases (Knuuttila and Boon, 2011; Meister and Upmeier zu Belzen, 2020; Göhner and Krell, 2022). To investigate the modeling process depicted, Krell et al. (2019) developed a coding manual that allows to analyze student activities during scientific modeling.

1.4. Simulation of complex systems

Exploring complex phenomena, like ecosystems in biology, is an essential part of science education. However, ecosystems are characterized by an effectively infinite number of variables that students cannot capture easily. A common tool to investigate the understanding processes of complex systems is simulations (Eilam, 2012; Grotzer et al., 2015; Hmelo-Silver et al., 2015; Yoon et al., 2018; Streiling et al., 2021). Simulations give access to complex systems, for example, by making the structure and dynamics observable. Due to this, simulations are employed in various studies, although there are major differences regarding the options for manipulation and the research aim. Often, these system simulations are used within interventional settings in order to improve systems thinking (Jordan et al., 2013; Hmelo-Silver et al., 2017; Yoon et al., 2017; Wiebe et al., 2019; Eilam and Omar, 2022; Rachmatullah and Wiebe, 2022; Torkar and Korfiatis, 2022). A slightly different approach is using simulations to foster systems thinking from a modeling perspective (Damelin et al., 2017; Bielik et al., 2022; Bowers et al., 2022). However, digital tools such as simulations can also be used as representations of complex systems within the context of non-interventional studies as integral parts of assessments (Sauvé et al., 2007).

2. Research questions and aim of the study

Given the current biodiversity crisis, understanding complex phenomena is of paramount importance. Systems thinking and scientific modeling are two different but likely interdependent perspectives on understanding complex phenomena. In the context of this study, we sought to examine the relationship between these concurrent perspectives more closely. Therefore, we address the following research questions:

1. Which systems thinking skills do students commonly use while analyzing a simulation of a dynamic ecological system?
2. Which activities of scientific modeling do students commonly use while analyzing a simulation of a dynamic ecological system?
3. How do students' systems thinking and scientific modeling activities interrelate in terms of co-occurrence during their analysis of a simulation of a dynamic ecological system?

3. Method

3.1. Simulation of a dynamic ecological system

Following these considerations, to engage students with a dynamic ecological phenomenon we have developed an interactive data-driven web application in R (R Core Team, 2022) utilizing the packages Shiny (Chang et al., 2022) and ggplot2 (Wickham, 2016). The web application illustrates the dynamics of an ecological system comprising six different species, including pasture grass, red clover, European rabbit, graylag goose, Canada goose, and red kite through an adjustable line graph showing the relative population sizes and thus their changes over time (see Figure 1). Decisive for the dynamic of the simulation are multiple predator–prey relationships, whereas the individual population sizes are estimated based on coupled differential equations by the R package deSolve (Soetaert et al., 2010). Initially, the simulation includes populations of pasture grass, red clover, European rabbit, graylag goose, and red kite, with the Canada goose being introduced later as an alien species. In consequence of the invasion, the dynamics of the ecological system are clearly disturbed and demonstrate emergent behavior in the extinction of the red kite. The participants' task was to infer the structure of the underlying food web based on the observed population dynamics. They were explicitly requested to develop a graphical model that explains the observed population trends by stating underlying relationships and how the species behave in relation to each other. Beyond that, the students did not receive any additional information about the species or instructions on how to proceed. The development of a graphical model was intended to ensure that the students keep their own modeling process in mind instead of reasoning on what they immediately see (Rellensmann et al., 2017). Within the web application, the participants could select the displayed time period and species at any time and as often as they wanted. Additionally, they could switch between one line graph for all species and individual graphs for each species (see Figure 1) to make it easier for the participants to examine individual relationships if desired. The correct solution to the students' task is represented in the food web in Figure 2, which served as basis for programming the simulation.

3.2. Data collection

To gain insights into the thinking process of the participants, we asked them to think aloud while exploring the given phenomenon (Ericsson and Simon, 1993; Zhang and Zhang, 2019). Students were tested individually, which avoids social influences and takes into account that the given scientific modeling category system (Krell et al.,

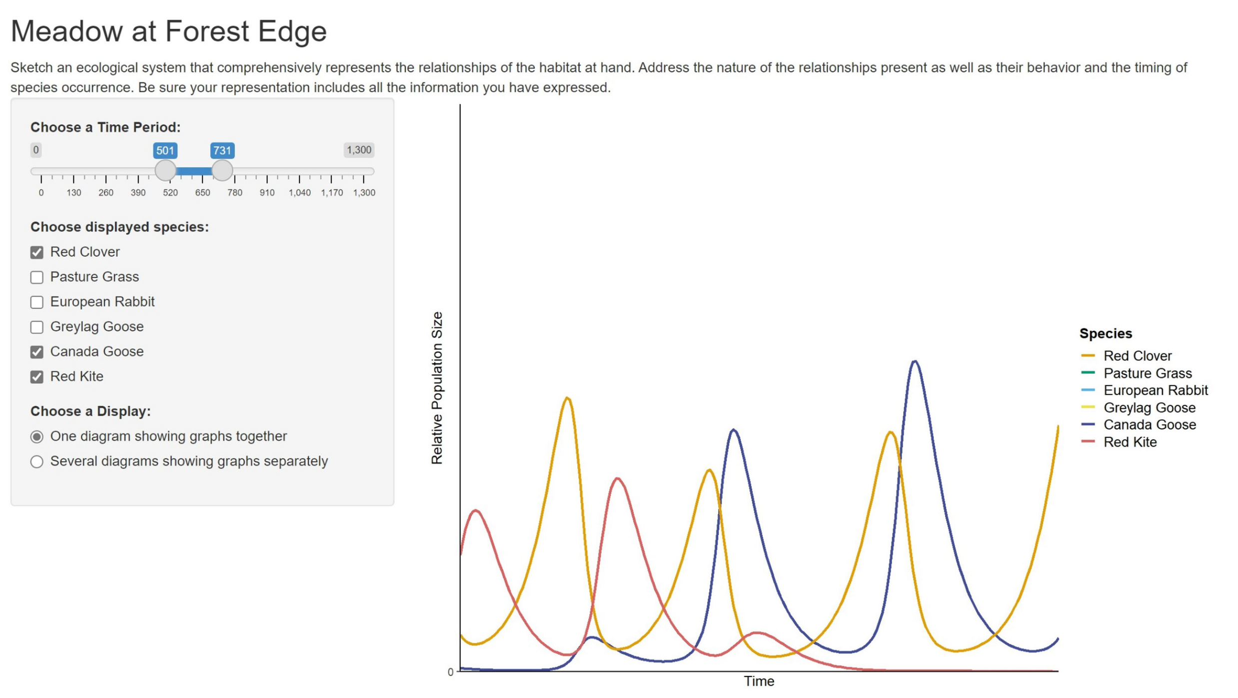

FIGURE 1
The simulation analyzed by the students.

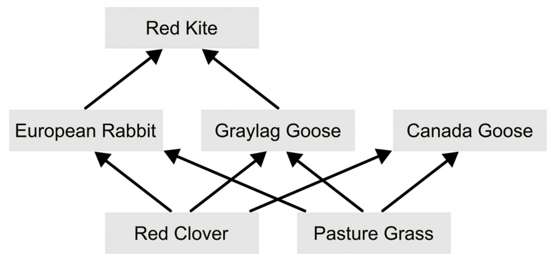

FIGURE 2
Food web underlying the simulation. It is not shown to the students.

2019) has been proved for individual problem solving, unlike group proceedings (Métrailler et al., 2008). The think-aloud protocol was explained to the participants and practiced on a simple and non-specialized topic before the actual survey started (Oh and Wildemuth, 2016). The students were reminded to think aloud and graphically develop their model during the survey, if necessary. For later evaluation, students' complete work was recorded (audio, screen recording). In addition, students were requested to develop their models on a tablet computer utilizing a digital whiteboard that enabled them to freely draw and illustrate their ideas (Microsoft Corporation, 2020). Since there was no time limitation, students could end the survey at any point they wanted, whether or not they judged the task to be completed. The mean processing time was $M = 43.3$ ($SD = 17.7$) minutes. Before further analysis, the collected data were processed through transcription of the audio files. Transcripts were supplemented by screenshots of the recorded graphical modeling process, where the audio transcript alone appeared to be ambiguous.

3.3. Sample

Nine German upper secondary level school students participated in our study (6 female and 3 male participants). Students' age ranged from 15 to 18 ($M = 16.7$) years. One-third of the students attended an advanced biology course, while the others took a basic biology course. Unfortunately, we do not have detailed records of individual students' current and completed biology teaching topics. However, all students were enrolled in the qualification phase for the *Abitur*, the highest secondary school diploma and higher education entry certificate in Germany. Ecology is one of three main subject areas in biology courses during this qualification phase. Courses at both levels include concepts regarding anthropogenic impacts on ecosystems and their consequences as well as concepts dealing with biodiversity and population dynamics (Kultusministerkonferenz, 2004). In addition, ecology is also part of the educational standards for the intermediate secondary level. Therefore, all students should in any case be familiar with basic concepts in the realm of ecology, for example regarding ecosystem organization, dynamic processes within ecosystems, and predator–prey relationships (Kultusministerkonferenz, 2005).

3.4. Coding scheme

To evaluate the students' statements, we performed a qualitative content analysis (Schreier, 2012; Mayring, 2014) using MAXQDA 2022 (VERBI Software, 2022), which is a well-established method for analyzing qualitative data whose value has already been proven in the context of modeling processes and systems thinking approaches (Gogolin and Krüger, 2018; Krell et al., 2019; Wellmanns and Schmiemann, 2022; Mambrey et al., 2022a). For the qualitative content analysis, we developed coding schemes based on the model of systems thinking by Mambrey et al. (2020) and the activities of scientific modeling described by Krell et al. (2019). In order to evaluate students' systems thinking in detail, we differentiated the levels of students' systems thinking described by Mambrey et al. (2020). We added multiple subcategories using a deductive approach to account for nuances in students' systems thinking (Schreier, 2012): We broke the level of direct relations down by distinguishing unidirectional relations and bidirectional relations. The level of linear relations was divided into linear relations bridging one element and linear relations bridging multiple elements. Similarly, we distinguished complex relations bridging one element from complex relations bridging multiple elements (see Mambrey et al., 2020). An overview of the coding scheme is given in Table 1. For the coding of students'

TABLE 1 Overview of students' levels of systems thinking in the context of a dynamic ecological system.

Level	Systems Thinking Skill		
	Identifying System Organization	Analyzing System Behavior	Modeling System Evolution
Reasoning Based on Simple Relations			
Unidirectional Relation	130	66	6
Bidirectional Relation	40	31	0
Reasoning Based on Linear Relations			
Linear Relation Bridging One Element	0	6	1
Linear Relation Bridging Multiple Elements	0	0	0
Reasoning Based on Complex Relations			
Complex Relation Bridging One Element	87	30	7
Complex Relation Bridging Multiple Elements	4	5	1

The levels, based on the framework of Mambrey et al. (2020), are listed in differentiated subcategories. Numbers represent the frequency of occurrence. Examples of student statements are available as Supplementary material.

scientific modeling activities, we adjusted the descriptions of the coding framework of Krell et al. (2019) to match our ecological context (Schreier, 2012). In contrast to our procedure for systems thinking, we used an inductive approach to extend the coding framework for scientific modeling by new categories. This inductive extension was necessary for the analysis of scientific modeling activities as the existing framework of Krell et al. (2019), unlike the systems thinking framework of Mambrey et al. (2020), required adaption for the presented multilayered phenomenon in an ecological context. We disclose the final coding frame for students' scientific modeling in the results section, as it is involved in answering the first research question. New categories are listed in Table 2 and marked with an asterisk.

3.5. Data analysis

Before coding the students' statements, two raters extensively discussed the existing frameworks of Krell et al. (2019) and Mambrey et al. (2020) and adapted them to this study and the ecological context. They then independently coded the data of a test participant and compared their coding result afterwards. Non-matching codes were analyzed, and the coding instructions were refined, as was the inductive differentiation of the category system in scientific modeling. An analysis of inter-rater reliability after re-coding of the test participant's statements revealed an almost perfect result for our coding schemes, for both systems thinking and scientific modeling ($\kappa > 0.8$) (Landis and Koch, 1977). As a result, the coding manual was classified as final and ready to use to code the participants' statements (Kuckartz and Rädiker, 2019). In the next step, the two raters independently coded all statements of the participating students. To ensure that the complete thinking process is considered, we used event-based coding (Ciesielska et al., 2018), whereas content correctness was no criterion (e.g., Krell et al., 2019). Consistency of the coding was checked by measuring inter-rater reliabilities for each participant and for systems thinking and scientific modeling separately using Kappa (Brennan and Prediger, 1981). In this regard, a coding was scored as matching if the segments of both codings were assigned to the same category and substantially overlapped. Overall, the analysis of the inter-rater reliabilities showed good results: For systems thinking, we achieved values of Kappa between 0.84 and 0.96 ($M = 0.88$) for eight students, which indicates an almost perfect agreement (Landis and Koch, 1977). For one student, neither rater found any statement related to systems thinking. For scientific modeling, the estimated values of Kappa are in the range of 0.73 and 0.86 ($M = 0.79$) for the nine students, which may be interpreted as substantial ($\kappa > 0.6$) to almost perfect ($\kappa > 0.8$) agreement (Landis and Koch, 1977).

To address our first two research questions, we analyzed the observed activities of scientific modeling and systems thinking using absolute and relative frequencies. In order to examine our third research question, which refers to the interrelationship between both perspectives, we created a contingency table. Using MAXQDA's Code Relations Browser (VERBI Software, 2022), we estimated the intersection of the applied codes of systems thinking with those of scientific modeling to reveal patterns of co-occurrence (Kuckartz and Rädiker, 2019).

4. Results

Overall, we coded 1,412 students' statements, which included 414 statements regarding systems thinking and 998 statements regarding scientific modeling. The number of segments per student varied widely, ranging from 103 to 292 ($M = 173$). Statements regarding systems thinking were most frequently (63.0%; absolute frequency of 261) assigned to the skill of identifying the system organization, which means, they describe the type of relationship between two or more species. For instance, one student stated: *"I would say now that European rabbits eat pasture grass."* (P. 4, Pos. 183). Also common were statements about analyzing the system behavior at 33.3% (absolute frequency of 138). Statements in this category describe a cause for a change in at least one population size usually by reference to another (changing) population size. An example of such a statement is: *"The Canada goose gained quite strongly in population in the following year, which is probably due to the high food supply of pasture grass."* (P. 5, Pos. 93). The third skill of systems thinking, modeling the system evolution, in our context entails developing a forecast of one or more population size changes, such as: "*My assumption is that if the* [red] *kite goes extinct, there must be more and more* [European] *rabbits because then there are no more predators.*" (P. 10, Pos. 287). Statements regarding modeling the system evolution were rare (3.6%; absolute frequency of 15). The evaluation of the named linkage (see Table 1) reveals frequent mentions of simple relations, including unidirectional and bidirectional relations. For instance, one student pointed out the bidirectional predator–prey relation between European rabbits and red clover: "*If the number of European rabbits is very low, the red clover can of course grow well and then it still rises here. There are more and more European rabbits because they find more to eat and at a certain point, the climax is reached by red clover* [...] *and then it* [red clover] *falls. And then at some point the European rabbit decreases as well.*" (P. 10, Pos. 45). Furthermore, students frequently used complex relations, typically bridging one element: "*Well, pasture grass and red clover is the food, especially for the European rabbit.*" (P. 2, Pos. 12). Whereby complex relations bridging multiple elements were less frequent. Students rarely referred to linear relations bridging one element, like: "*Then the European rabbit eats the red clover and if there is a lot of red kite, then there is little of European rabbits, which means that the population* [of red clover] *increases. And conversely, when there are few European rabbits, there is a lot of red clover.*" (P. 5, Pos. 112), whereas linear relations bridging multiple elements were never mentioned. For additional examples of students' statements on systems thinking see the Supplementary material.

The surveyed activities of scientific modeling were classified as follows: 62.5% exploration (absolute frequency 624), 6.4% activation of analogies and experiences (absolute frequency 64), 10.3% mental modeling (absolute frequency 103), 15.4% development (absolute frequency 154), and 5.3% prediction (absolute frequency 53). In addition to the deductively derived categories (Krell et al., 2019), six categories were added by induction. Five of these categories follow a logical addition (Schreier, 2012). For example, negating statements about pattern, like: "[...] *however, bears no resemblance to either of the other two* [graphs of red clover and pasture grass], *i.e., the European rabbit*" (P. 8, Pos. 147), were added in the newly included category 5b: Student negates presence or detection of a pattern. Statements describing a model's inconsistency and/or inconsistency between model and observation, such as: "*That means that* [the drawn arrow]

TABLE 2 Overview of students' activities in the process of scientific modeling in the context of a dynamic ecological system.

Phase	ID	Activity	Category with Explanation	Frequency
Exploration	1	Perception of Phenomena	Student describes observed behavior of the ecological system as spontaneous or incomprehensible.	53
	2	Arbitrary Exploration of the System	Student arbitrarily chooses a time interval and/or species and/or display mode.	78
	3a	Description of Observations	Student describes observed behavior of the ecological system without recognizing any pattern.	145
	3b*	Notes on Observations	Student takes notes on the observed behavior of the ecological system (see 3a).	17
	4	Purposive Exploration of the System	Student selects a time interval and/or species and/or display mode to detect a pattern in the behavior of the ecological system.	153
	5a	Recognition of Pattern	Student recognizes or confirms a pattern (see 4).	130
	5b*	Negation of Pattern	Student negates presence or detection of a pattern (see 4).	21
	5c*	Notes on Pattern	Student takes notes on the recognized, confirmed, or negated pattern.	27
–	6a	Activation of Analogies and Experiences	Student verbalizes ideas about the organization and/or behavior of the ecological system and/or thinks about these ideas aloud, based in each case on analogies and/or experiences.	64
–	6b*	Mental Modeling	Student verbalizes ideas about the organization and/or behavior of the ecological system and/or thinks about these ideas aloud, based in each case on observations of the ecological system.	103
Development	7	Analogy and Experience-Based Model Development	Student develops graphical model of the ecological system based on analogies and/or experiences (see 6a).	8
	8	Design-Based Model Development	Student develops model to improve internal logic, functionality, or aesthetics.	15
	9	Observation-Based Model Development	Student develops graphical model retrospectively based on observations of the ecological system.	85
	10	Observation-Based Model Rejection	Student rejects model retrospectively based on observations of the ecological system.	0
	11	Design-Based Model Evaluation	Student evaluates model regarding internal logic, functionality, or aesthetics.	1
	12	Observation-Based Model Evaluation	Student compares model with observations of the ecological system.	12
	13a	Confirmation of Model Consistency	Student confirms model consistency (see 11) and/or consistency between model and observations (see 12).	29
	13b*	Denial of Model Consistency	Student identifies model inconsistency (see 11) and/or inconsistency between model and observations (see 12).	4
Prediction	14	Generation of Predictions	Student deduces hypothesis based on the model about the organization and/or behavior of the ecological system.	13
	15	Purposive Manipulation of the System	Student selects a time interval and/or species and/or display mode based on a hypothesis (see 14).	18
	16	Confirmation of Predictions	Student confirms hypothesis (see 14) by observing a pattern within the behavior of the ecological system (usually through 15).	10
	17	Falsification of Predictions	Student falsifies hypothesis (see 14) by observing a pattern within the behavior of the ecological system (usually through 15).	5
	18a*	Model Modification Based on Confirmed Prediction	Student modifies model based on a confirmed hypothesis (see 16).	5
	18b	Model Modification Based on Falsified Prediction	Student modifies model based on a falsified hypothesis (see 17).	2
	19	Prediction-Based Model Rejection	Student rejects model based on a falsified hypothesis (see 18).	0

The coding scheme is based on the existing framework of Krell et al. (2019). New categories are marked with an asterisk. Examples of student statements are available as Supplementary material.

makes no sense to me here. The red kite decreases very strongly, very suddenly, and the graylag goose decreases only very slowly." (P. 3, Pos 192), were covered by the new category 13b. Similarly, student statements about modifying the model based on confirmed hypothesis, like: "*This allows us to conclude that the Canada goose feeds a bit on the red clover.* [Student writes down] *Canada goose eats red clover.*" (P. 3, Pos 167–169), were added as affirmation in category 18a. During the survey, students repeatedly took written notes in their representation regarding descriptions and patterns of the ecological system. For example, one student pointed out while observing the system behavior: "*I'm writing this down now. Pasture grass increases at 500, then decreases again.*" (P. 3, Pos. 55–56). To differentiate these activities from the existing categories, which solely pertain to verbal expressions, we added the categories 3b: Student takes notes on the observed behavior of the ecological system, see previous student statement, and 5c: Student takes notes on the recognized, confirmed, or negated pattern. Another new activity that emerged within the process of scientific modeling is described in category 6b: Mental modeling, as the students in our study did not always document their ideas about the model mechanism in written form, opting to express them verbally instead. For instance, a student verbalizes the assumed correlation between the population dynamics of the Canada goose and its food sources: "*I would have thought that if I added these two feed together, I could conclude that by having a lower feed supply, I would also have fewer populations* [of Canada geese]." (P. 6, Pos 160). Such verbal expressions were even observed when the students were reminded to create a graphical representation. Table 2 shows the full coding scheme, including observed frequencies. Exemplary statements from the present study for each category of scientific modeling are provided in the Supplementary material.

To answer research question three on how students' systems thinking and scientific modeling activities interrelate when they examine the dynamic ecological system, we determined co-occurrences of coded segments of both perspectives (see Table 3). This analysis revealed several noticeable interrelations. During system exploration, students demonstrated systems thinking almost exclusively in the area of system behavior and during the interaction with data patterns (modeling activities 5a-c). When students addressed notions referring to the system organization, it was in the context of deducing hypothesis-based graph interactions (modeling activity 4). In the phases of model development, we frequently observed systems thinking. Especially during the broadly observed phases of developing and refining the model, students dealt with the system organization and behavior. In both scientific modeling phases, system exploration and model development, no modeling of the system evolution took place. This changes for the development of predictions, where all three skills of systems thinking were observable. The system modeling, however, is almost entirely tied to the activity of using the model to deduce hypotheses. In addition, activities 6a, referring to the verbalization of analogies and experiences, and 6b, covering the development and usage of mental models, have a special status. During the activation of analogies and experiences (modeling activity 6a), students extensively refer to notions related to the system organization and occasionally deal with concepts regarding the system behavior as well. The mental modeling (modeling activity 6b) was accompanied by systems thinking skills of all kinds. While the system behavior and especially the system organization predominate, modeling system evolution was also observed at least occasionally.

5. Discussion

In this study, we confronted students with a dynamic ecological phenomenon in order to examine their systems thinking and scientific modeling as well as the interrelations between these perspectives. The results enable us to provide a detailed account of the students' comprehension process of a complex and dynamic system.

5.1. Systems thinking

We were able to assess students' systems thinking using a coding scheme based on the framework of Mambrey et al. (2020). However, when examining the frequency of occurrence, it was observed that activities of identifying the system organization and analyzing the system behavior were much more frequent than modeling the system evolution. This pattern may be attributed to a difference in the cognitive perspective, as identifying the system organization and analyzing the system behavior requires the application of broad, globally applicable skills, whereas modeling the system evolution demands mental application specific to the task at hand. Students must use their gained knowledge about the system to derive predictions about system development and future states (Mehren et al., 2018), which also requires imagination and creative thinking (Mambrey et al., 2022a). Moreover, and due to the openness of the survey, the task may lack the imperative character necessary to evoke prediction generation. In our opinion, it could therefore be highly rewarding to fill this gap by adding tasks in future research that demand prediction generation, even when this means structuring the process through individual instructions or prompts. In order to analyze students' systems thinking in detail, we also examined the linked structure of relations they took into account. First, and in line with previous results (Strogatz, 2001; Gotwals and Songer, 2010; Hokayem, 2016; Mehren et al., 2018; Mambrey et al., 2022b), we observed that students' mentions of low linked relationships greatly outweighed the references to high linked relations connecting multiple elements. When examining the specific types of relations, there was a particularly high occurrence of unidirectional, bidirectional, and complex relations bridging one element. Whereas complex relations bridging multiple elements or linear relations were rarely mentioned. We suppose this pattern arises from a moderate linking performance in combination with a sound understanding of isolated predator–prey relationships among the participants (Grotzer and Basca, 2003; Sommer and Lücken, 2010; Mambrey et al., 2022a). Indeed, students often referred to feeding relationships commonly covered in class, such as a predator–prey and competitive relationship, with and without naming the competing food source (NGSS Lead States, 2013). This may even be a good strategy to identify the system organization. However, it is not possible to understand the emergent extinction of the red kite by analyzing individual predator–prey or competitive relationships. Even though the presented phenomenon demands an understanding of emergence, we have not explicitly demanded this and a food web, as typical representation of the trophic relationships within an ecosystem, does not directly reflect this emergent behavior. Therefore, future systems thinking research could focus on systems demonstrating emergent behaviors or systems with an ever-changing system organization in order to evoke more complex systems thinking.

5.2. Scientific modeling

We successfully utilized the scientific modeling framework developed by Krell et al. (2019) to analyze students' scientific modeling activities in the context of a dynamic ecological system: Our analysis revealed that students were extensively engaged in the exploration of the system, which is consistent with previous research (Göhner and Krell, 2022). Frequently, we observed students taking notes during exploration, particularly when summarizing or describing an observed

TABLE 3 Contingency table of the interrelationship between scientific modeling and systems thinking.

			Identifying System Organization						Analyzing System Behavior						Modeling System Evolution					
			Unidirectional Relation	Bidirectional Relation	Linear Relation Bridging One Element	Linear Relation Bridging Multiple Elements	Complex Relation Bridging One Element	Complex Relation Bridging Multiple Elements	Unidirectional Relation	Bidirectional Relation	Linear Relation Bridging One Element	Linear Relation Bridging Multiple Elements	Complex Relation Bridging One Element	Complex Relation Bridging Multiple Elements	Unidirectional Relation	Bidirectional Relation	Linear Relation Bridging One Element	Linear Relation Bridging Multiple Elements	Complex Relation Bridging One Element	Complex Relation Bridging Multiple Elements
Exploration	1	Perception of Phenomena																		
	2	Arbitrary Exploration of the System																		
	3a	Description of Observations																		
	3b*	Notes on Observations																		
	4	Purposive Exploration of the System		1			4		1											
	5a	Recognition of Pattern							16	9	1		3							
	5b*	Negation of Pattern							1	2			1							
	5c*	Notes on Pattern							5	3										
	6a	Activation of Analogies and Experiences	15	2			9		4				1							
	6b*	Mental Modeling	37	10			18	2	16	10	1		15	2					4	
Development	7	Analogy and Experience-Based Model Development		1			3													
	8	Design-Based Model Development	2				1		1											
	9	Observation-Based Model Development	60	20			38	2	20	9	1		7	3						
	10	Observation-Based Model Rejection																		
	11	Design-Based Model Evaluation	1																	
	12	Observation-Based Model Evaluation	2				7			1			1							
	13a	Confirmation of Model Consistency	5	5			6		6	3	1		4							
	13b*	Denial of Model Consistency							2											
Prediction	14	Generation of Predictions	1												6		1		5	1
	15	Purposive Manipulation of the System	1																	
	16	Confirmation of Predictions	1	1			1		2	1			6							
	17	Falsification of Predictions	2												1					
	18a*	Model Modification Based on Confirmed Prediction	4				2				2									
	18b	Model Modification Based on Falsified Prediction		1																
	19	Prediction-Based Model Rejection																		

The frequency of the overlaps is given in absolute numbers. The coding scheme for scientific modeling is based on the existing framework of Krell et al. (2019). The systems thinking skills and levels are based on the framework of Mambrey et al. (2020).

behavior (modeling activity 3) and recognizing or confirming data patterns (modeling activity 5). Therefore, we inductively added categories in each phase to account for this behavior (Schreier, 2012). We suppose that taking notes may be functional or even necessary in some situations due to the system's complexity, which includes numerous not directly recognizable relations. Some students probably used this strategy as a cognitive aid to visually represent knowledge about specific relations (Peper and Mayer, 1986). Generally speaking, prior knowledge in the form of analogies and experiences (modeling activity 6a) is frequently observed during scientific modeling (Krell et al., 2019; Meister and Upmeier zu Belzen, 2020). Besides exploring the system or reflecting on prior knowledge (modeling activity 6a), students comprehensively dealt with graphical model development. They frequently incorporated findings from their observations of the system (modeling activity 9) and evaluated the model consistency (modeling activities 11, 12, 13). By extending the coding scheme to differentiate students who found consistency (modeling activity 13a) from those detecting inconsistency between their graphical model and the systems behavior, we noted an interesting pattern: At this point of model development, students almost never detect inconsistency. This could be the case, as they frequently perform mental modeling instead of recording their ideas about the model in a graphic format. Indeed, this process of mental modeling is a key phase of scientific modeling (Clement, 1989; Nersessian, 2008; Gilbert and Justi, 2016) and has been observed in previous modeling studies (Meister and Upmeier zu Belzen, 2020). We added a category to our coding scheme to account for this behavior (modeling activity 6b), though the frequency of occurrence of this activity certainly raises the question of the underlying substructure of mental modeling for future research. To investigate this question, analyzing students' individual modeling processes will help determine the position and weight of mental modeling within the overall process of scientific modeling (e.g., Göhner and Krell, 2022). In particular, there is evidence that the mental model and the emerging graphical representation of the model may not be fully equivalent (Chandrasekharan and Nersessian, 2015).

Where we found limited evidence, however, was in the phase of predictive model usage. This could be the case because students often do not fully understand the use of models for prediction, as noted by Gogolin and Krüger (2018). In addition, previous research indicates that model application can be challenging (Campbell et al., 2013; Passmore et al., 2014; Krell and Krüger, 2016; Meister and Upmeier zu Belzen, 2020; Göhner and Krell, 2022). The lack of predictive model usage may also be an expression of students' struggling to generate hypotheses from prior knowledge, their model in progress or previous observations of the system behavior. This would fit the results and the model of Klahr and Dunbar (1988), who assume that exploration without hypothesis is a strategy to search for some kind of pattern within the data and is applied if the generation of hypotheses fails. Surprisingly, when students derived hypotheses, they modified their model not only in response to falsified hypotheses but also in response to confirmed hypotheses (modeling activity 18b). This may be due to the complexity of the system, as new knowledge about individual relationships within the system may require adjustments to the model or allow for model enhancements without necessitating a complete overhaul of the previous understanding. In addition, confirming findings may be suitable not only to the recent hypothesis but also to previous ideas which appear more promising or worthy of investigation (Klahr and Dunbar, 1988).

5.3. Interrelation between scientific modeling and systems thinking

From the combined analysis of systems thinking and scientific modeling, we can identify the following relationships in our study: During the exploration of the ecological system, we rarely observed systems thinking. In the event of pattern recognition, we detected systems thinking almost exclusively with the objective of analyzing the system behavior. Otherwise, systems thinking occurred frequently during model development. We suppose that these findings perfectly illustrate a central difference in the perspectives of systems thinking and scientific modeling. While the former includes the description and explanation of complex phenomena as well as the prediction thereof, the latter additionally involves incidental perception as the early phase of exploration. Another difference in perspective is that systems thinking often describes several skills that relate to specific system properties (Mambrey et al., 2020; Momsen et al., 2022), whereas scientific modeling primarily focuses on the process and activities of modeling the initial natural phenomenon or system. However, identifying the system organization and analyzing the system behavior are mandatory preconditions for successfully developing a model that explains the phenomenon or system (Passmore et al., 2014; Gouvea and Passmore, 2017; Krell et al., 2019). Our results match this assumption, as the students frequently utilize both skills of identifying the system organization and analyzing the system behavior during model development. Another result of the independent coding of systems thinking and scientific modeling was the third skill of systems thinking, modeling the system evolution, being closely linked to the scientific modeling activity of hypothesis generation. This even makes sense, as the former entails statements developing a forecast of one or more population size changes, while the latter covers statements deducing predictions based on an existing model (Clement, 1989; Justi and Gilbert, 2002; Giere et al., 2006; Gilbert and Justi, 2016; Krell et al., 2019; Upmeier zu Belzen et al., 2019). The juxtaposition makes clear that the definition of modeling the system evolution and hypothesis generation in the realm of scientific modeling are closely related. It is therefore not surprising that beyond this, modeling the system evolution as one skill of systems thinking only appeared in conjunction with the phase of mental modeling. This seems even plausible, as the modeling process starts in mental space and can involve cycles of development, evaluation, and modification before any graphic development (Meister and Upmeier zu Belzen, 2020). And indeed, students generally utilize all systems thinking skills in the process of mental modeling. Considering the ratios throughout the mental modeling phase, the participants are more often involved in analyzing the system behavior than in identifying the system organization, while identifying the system organization appears slightly more frequently during the graphical production phase. Perhaps this may be explained by a finding of Mambrey et al. (2022a), who demonstrated that a food web as representation is strongly associated with identifying the system organization but rather no reference for students when analyzing the system behavior or modeling the system evolution. This may explain our observations, as most students drew food webs as models to represent the ecological system. As this type of representation does not provide quantitative information about population growth or decline (Begon and Townsend, 2021), it may, in fact, not evoke thinking about the system behavior. In contrast, the line graph we used in our task focuses on the population dynamics and should thus be a stronger trigger for analyzing the system behavior. Our data clearly support that assumption.

6. Limitations and implications

Our study is limited in some areas that we would like to discuss briefly in the following: to gain a comprehensive understanding of students' systems thinking and scientific modeling, we provided each participant individual time for analyzing the ecological system simulation. Hence and due to the task complexity, it was not possible to test multiple systems. Therefore, the results may be limited regarding potential context effects (Grotzer and Basca, 2003; Verhoeff et al., 2013; Mambrey et al., 2020). Furthermore, our analysis focused on the general expression of systems thinking and scientific modeling. In consequence, we did not assess students' content knowledge explicitly, even though modeling activity 7 does provide evidence of the incorporation of analogies and experiences that directly relate to the process of model development. In addition, our coding scheme as well as the underlying framework of Mambrey et al. (2020) do not address systems thinking from a perspective of system properties. As individual system properties, including dynamic changes and susceptibility to disruptive factors like invasive species, play an important role in our simulation, this perspective may be interesting for future research. Furthermore, characteristics of our simulation may also impact students' thinking. For example, the simulated population dynamics may have drawn students' attention on thinking about the system behavior in particular. We found that students rarely mentioned emergent effects resulting from complex interrelationships, as well as predictions about future system states or behaviors. One reason for this may be that the task and the simulation do not encourage this explicitly. Hence, future research should emphasize on systems with greater changes in their dynamics and complex emergent effects. Additionally, it would be worthwhile to include tasks that stimulate the prediction of these changes in system development.

Although we did not analyze the students' individual procedures yet, we wish to discuss possible implications for engaging students in systems thinking and scientific modeling. Our results imply that a task involving students in the exploration of a dynamic system to deduce the system structure seems suitable to evoke systems thinking and modeling insofar as the students develop models. However, the generation of predictions and, consequently, the modeling of the system evolution as well fell short of our expectations. We suppose that the regular oscillatory nature in population dynamics is too foreseeable, even if the introduction of the invasive Canada goose was a functional disturbance. In this regard, it may be beneficial to utilize even less predictable system dynamics, for example, by modeling alternative stable states or multiple regime shifts in ecosystems (Scheffer and Carpenter, 2003), to focus on the cyclic nature of modeling through predicting outcomes and modifying the model. However, it remains open whether all students used the same approach or if they showed distinctive styles of scientific modeling and systems thinking (e.g., Meister and Upmeier zu Belzen, 2020; Göhner and Krell, 2022). In order to answer this research question, it might be beneficial to analyze the individual chronological sequences of students' proceedings. Additional insights could be revealed by analyzing students' drawings, as individual students also created representations other than food webs. In this context, we are especially interested in whether different types of representations correlate with distinct patterns of systems thinking and how students account for the system's dynamic behavior in their representations.

Data availability statement

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

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

AL, JT, and PS: conception and design of the study and manuscript revision. AL and JT: development of the test instrument and manuscript writing. AL: data collection and data analysis. PS: supervision. All authors contributed to the article and approved the submitted version.

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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.

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Supplementary material

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EDITED BY
Laura Zangori,
University of Missouri, United States

REVIEWED BY
Sarah Digan,
Australian Catholic University, Australia
Christina Krist,
University of Illinois at Urbana-Champaign, United States
Jaime Sabel,
University of Memphis, United States

*CORRESPONDENCE
Zach Ryan
✉ zryan@iu.edu

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Investigating students' development of mechanistic reasoning in modeling complex aquatic ecosystems

Zach Ryan[1]*, Joshua Danish[1], Jinzhi Zhou[1], Christina Stiso[1], Danielle Murphy[2], Ravit Duncan[2], Clark Chinn[2] and Cindy E. Hmelo-Silver[1,2]

[1]School of Education, Indiana University – Bloomington, Bloomington, IN, United States, [2]School of Education, Rutgers University, New Brunswick, NJ, United States

Introduction: This study reports on a classroom intervention where upper-elementary students and their teacher explored the biological phenomena of eutrophication using the Modeling and Evidence Mapping (MEME) software environment and associated learning activities. The MEME software and activities were designed to help students create and refine visual models of an ecosystem based on evidence about the eutrophication phenomena. The current study examines how students utilizing this tool were supported in developing their mechanistic reasoning when modeling complex systems. We ask the following research question: *How do designed activities within a model-based software tool support the integrations of complex systems thinking and the practice of scientific modeling for elementary students?*

Methods: This was a design-based research (DBR) observational study of one classroom. A new mechanistic reasoning coding scheme is used to show how students represented their ideas about mechanisms within their collaboratively developed models. Interaction analysis was then used to examine how students developed their models of mechanism in interaction.

Results: Our results revealed that students' mechanistic reasoning clearly developed across the modeling unit they participated in. Qualitative coding of students' models across time showed that students' mechanisms developed from initially simplistic descriptions of cause and effect aspects of a system to intricate connections of how multiple entities within a system chain together in specific processes to effect the entire system. Our interaction analysis revealed that when creating mechanisms within scientific models students' mechanistic reasoning was mediated by their interpretation/grasp of evidence, their collaborative negotiations on how to link evidence to justify their models, and students' playful and creative modeling practices that emerged in interaction.

Discussion: In this study, we closely examined students' mechanistic reasoning that emerge in their scientific modeling practices, we offer insights into how these two theoretical frameworks can be effectively integrated in the design of learning activities and software tools to better support young students' scientific inquiry. Our analysis demonstrates a range of ways that students represent their ideas about mechanism when creating a scientific model, as well as how these unfold in interaction. The rich interactional context in this study revealed students' mechanistic reasoning around modeling and complex systems that may have otherwise gone unnoticed, suggesting a need to further attend to interaction as a unit of analysis when researching the integration of multiple conceptual frameworks in science education.

KEYWORDS

science education, modeling, complex systems, elementary education, design-based research (DBR)

Introduction

Scientific modeling remains a critical practice in the process of understanding phenomena through scientific inquiry (National Research Council, 2012; Pierson et al., 2017). A persistent challenge for science educators is to teach young students modeling practices in the context of complex systems, where disparate connections and relations in a system make up a network of emergent causal processes that produce observable scientific phenomena, such as eutrophication in an aquatic ecosystems (Hmelo-Silver and Azevedo, 2006; Assaraf and Orion, 2010). Past science education research demonstrates that elementary students have the capacity to effectively engage with complex systems concepts when supported by strong scaffolds in instruction which support students' engagement in scientific modeling practices (Yoon et al., 2018). However, mechanisms remain a challenging aspect of scientific explanations for young learners to articulate because students often do not recognize the underlying hidden relationships between elements of a system (Russ et al., 2008).

In order to scaffold the alignment of students' modeling practices with systems thinking, we developed the *modeling and evidence mapping environment* (MEME) software tool (Danish et al., 2020, or see http://modelingandevidence.org/), which explicitly scaffolds the *Phenomena, Mechanism, and Components (PMC) framework* (Hmelo-Silver et al., 2017a), a systems thinking conceptual framework designed to support students in thinking about these three levels of biological systems, within a modeling tool (see Figure 1). MEME was created to allow students to create and refine models of a biological ecosystem through a software interface. The aim of the current study is to examine how students utilizing this tool reason about mechanisms when iteratively modeling complex systems. Towards these ends, we investigate the following research question: *How do designed activities within a model-based software tool, scaffolded with the PMC framework, support the integration of complex systems thinking and the practice of scientific modeling for elementary students?*

Theoretical framework

Our work is grounded in sociocultural theories of learning (Vygotsky, 1978), which assert that the cultural contexts and communities that people interact in are inseparable from the process of learning, and therefore must be rigorously analyzed. We had a particular focus on how the designed elements of a learning environment mediate (i.e., transform) the ways in which students reason about ideas in science. *Mediation* here refers to something in an environment that comes between a subject and their goal, and consists of mediators, or the tools, rules, community, and divisions of labor which support and transform students' participation in an activity as they pursue particular goals (Engeström, 2001; Wertsch, 2017). A key feature of mediation is that it constitutes a reciprocal relationship between subjects and objects. So, while a mediator certainly shifts how we pursue certain goals in activity, we in turn transform the mediators through taking them up

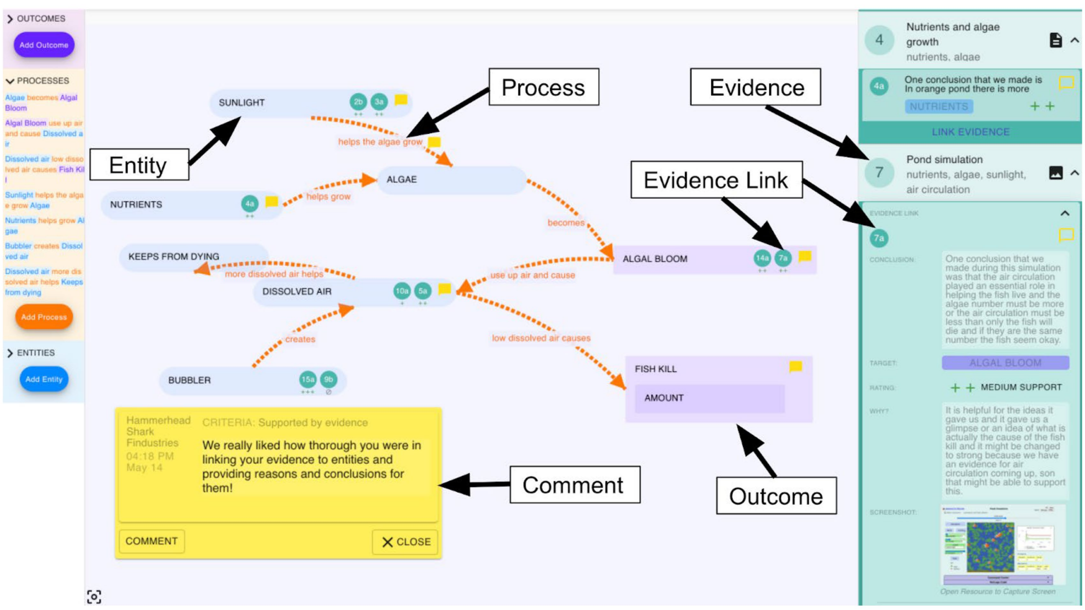


FIGURE 1
Screenshot of the MEME interface with PMC scaffolds highlighted.

and appropriating them. This appropriation internalizing them into our own practices, and of course the goals of our activity further shape how we recognize the potential value or role of the mediator (Wertsch, 2017). For instance, while particular features in MEME, such as being able to link evidence in a model, might mediate students' mechanistic reasoning about a complex system, that mechanistic reasoning will in turn affect how they utilize and take up that particular feature in their collaborative model creation and revision.

In the larger project this work is situated in, titled Scaffolding Explanations and Epistemic Development for Systems (SEEDS), our primary goal was to design a software tool and set of collaborative inquiry learning activities which integrated support for multiple theoretical frameworks to foster robust science learning. Specifically, we aimed to bridge complex systems thinking (Hmelo-Silver and Azevedo, 2006), scientific modeling (National Research Council, 2013), epistemic criteria (Kuhn, 1977; Murphy et al., 2021), and grasp of evidence (Duncan et al., 2018) in order to integrate the use of evidence in creating and revising models of a complex system (an aquatic ecosystem) in late elementary classrooms. We therefore adopted a design-based research approach (Cobb et al., 2003; Quintana et al., 2004) in order to pursue these goals in order to systematically and iteratively test how these frameworks integrated within a modeling unit directly in the context of a 5th/6th grade classoom. We then iteratively implemented and revised our design throughout the study, streamlining the software and classroom prompts to help explore the potential of this approach.

Complex systems thinking

Complex systems have become increasingly relevant in science education and are highlighted by the Next Generation Science Standards (NGSS) as an important crosscutting concept because of their value in understanding a wide range of emergent phenomena (NRC, 2013). Learning about complex systems often proves difficult for students because they struggle to view the system from multiple perspectives, and assume it is centrally controlled as opposed to emerging from many simple local behaviors (Jacobson and Wilensky, 2006). To learn how observable phenomena emerge in a complex system, learners must attend to, study and represent the underlying mechanisms at play in a system, rather than just the surface-level observable components or details (Wilensky and Resnick, 1999; Assaraf and Orion, 2010). This focus is necessary for students to understand how systems function instead of focusing solely on their components or individual functions (Hmelo-Silver and Azevedo, 2006). Other important aspects of complex systems that are valuable for learners to understand include multiple levels of organization, numerous connections between entities, invisible elements that connect the system, and dynamic causal chains that make up the interactions within a system. These aspects can make it difficult for young learners to begin to understand how a system functions (Jacobson and Wilensky, 2006; Hmelo-Silver et al., 2007; Chi et al., 2012). Additionally, complex systems have emergent properties that are only observable when attending to multiple parts of the system interacting and can go unseen when only considering individual elements (Wilensky and Resnick, 1999). As a result, reasoning about complex systems can often overwhelm students and create too high of a cognitive load for students to effectively reason about.

One example of this – and the focus of this study – is aquatic ecosystems. In the present study, we introduce students to a pond-based aquatic ecosystem where they can observe the eutrophication phenomena in action. This system consists of fish interacting with other entities including, but not limited to, algae, plants, predators, and levels of dissolved oxygen present in the water. When something new is introduced to the system to disrupt these interactions, it can be catastrophic for the system for reasons that may not be immediately salient to learners who may just study one aspect of the system, such as students thinking fish get sick and die because of pollution in the water rather than the system falling out of equilibrium. In our imaginary yet realistic context, nutrient runoff from local farms has washed into a local body of water during heavy rainfall, diminishing fish populations during the summer months when the algae blooms. Students are tasked with developing scientific models to represent and explain this phenomena informed by various pieces of data and evidence that we provide to them via the MEME interface. It is a challenge for many students to discern the cause of the fish population decline from disparate pieces of data and evidence, though this is a more realistic experience of scientific analysis than being presented with all of the key information in one tidy package. Our design goal was to create both a software tool (MEME) and a set of activities to scaffold students' reasoning about this complex system.

Prior research on systems thinking has demonstrated that scholars and educators should focus on identifying instructional tools and activities that can explicitly mediate students' reasoning about complex systems, helping orient learners to the need to understand the system on multiple levels (Danish, 2014). In this context, we grounded our learning designs in the PMC conceptual framework, which has been shown to support students in engaging with key dimensions of systems (Hmelo-Silver et al., 2017a; Ryan et al., 2021). The PMC framework is a way to support students in explicitly thinking about three key levels of biological systems (phenomena, mechanisms, and components) that can help make many of the underlying relationships within a system salient. In the PMC framework, students frame their ideas around a given *phenomena* (e.g., an aquatic ecosystem), uncover underlying causal *mechanisms* that undergird a phenomena (e.g., excess nutrients in a pond causing an algal bloom), and investigate the *components* (e.g., fish, algae, and dissolved oxygen) that interact to create the mechanisms. Activities, scaffolds, and tools that align with the PMC framework explicitly represent complex systems through the combinations of various components within a system, and represent the relationships between them through descriptive mechanisms, resulting in students' developing a metacognitive awareness of the system and its various, disparate features (Saleh et al., 2019). To help orient students towards the importance of these levels (P, M, and C), we designed MEME to make them required and salient as students represented the system they were exploring.

Student modeling of complex systems

Scientific modeling has been long established as a core scientific practice relevant to young students' science learning (Lehrer and Schauble, 2005; National Research Council, 2012). Modeling in this context refers to a representation created in order to abstract the causal mechanisms of complex phenomena, and highlight particular causal chains and features to scaffold scientific reasoning and prediction (Schwarz et al., 2009). Therefore, many educators focus on modeling as a practice that involves creating and revising a representation rather than a single representational product. Nonetheless, models can take many forms including a diagram of the water cycle illustrating how water shifts and changes form in response to environmental stimuli, or a food web highlighting interactions between organisms in an ecosystem.

When one constructs a scientific model, choices must be made in how simple or complex a model should be, and what features of a phenomenon should be highlighted. For students new to the practice of modeling, these choices can be overwhelming. When teaching modeling to students, it is necessary to not only teach students how to create a good model, but to help them to understand the epistemics of what makes a scientific model good according to the scientific community (Barzilai and Zohar, 2016). We draw on the idea of epistemic criteria, or the standards established in the scientific community of what constitutes a valid and accurate product of science (Pluta et al., 2011). For instance, in our projects we worked with the students to establish a set of epistemic criteria about what constitutes a good scientific model, including model coherence, clarity, and how well the model fits with evidence. This allowed for streamlined goals for students to work towards when constructing their models, such as fitting their models to evidence, which in turn supported the validity of the components and mechanisms they represented in their models. We then represented these criteria within MEME in the interface used for students to give each other feedback.

Pluta et al. (2011) emphasize that students' understanding of epistemic criteria is interconnected with their understanding of modeling. They emphasize that if students "hold that models are literal copies of nature, they will likely fail to understand why models need to be revised in light of evidence" (p. 490). Models are not static entities and require revision as scientists' understanding of phenomena changes. With this epistemic criteria in mind, we aligned our activity designs with the grasp of evidence framework which focuses on developing students' understanding of how scientists construct, evaluate and use evidence to continually develop their understanding of phenomena, such as creating and revising models (Ford, 2008; Duncan et al., 2018).

We focused specifically on how students, who are not yet experts in scientific inquiry, interpreted evidence and determined what parts of data are significant to represent or revise in their models (Lehrer and Schauble, 2006). In fact, a primary feature in MEME was a repository of data and reports which we created for the unit, which was directly embedded into the software interface for students to explore as they created and refined their models. Students were able to directly read over empirical reports and data, and decide what reports were useful evidence that either supported or disproved claims they made about the aquatic ecosystem (Walton et al., 2008).

As the unit went on, students were tasked with revising and iterating on their model, based on their interpretation of new sets of evidence introduced to them. Students added new elements or modified existing elements in their models, and could directly link a piece of evidence to a specific feature of their model to support their reasoning. Not only were students learning to interpret and reason around empirical evidence, but the evidence they reviewed was grounded within the PMC framework as well. As students began to interpret multiple, disparate pieces of data about the aquatic ecosystem, they began to make claims about the system, and represented this in their models through various components and mechanisms.

In the current study, the practice of modeling included creating a box and arrow representation of the aquatic ecosystem (see Figure 1), collaboratively evaluating it alongside peers, and iterating on models based on peer and expert feedback (Danish et al., 2021). Models in MEME build on the idea of simple visual representations, such as stock-and-flow diagrams (Stroup and Wilensky, 2014) and concept maps (Safayeni et al., 2005), both of which can help students to link disparate ideas, and grow more complex as they iteratively refine them while also supporting the development of more coherent systems understanding. The difference here that distinguishes MEME from other model-based tools, is that the software interface was intentionally designed to directly bridge students' developing epistemic criteria around the practice of modeling through a comment feature where peer feedback was given based off of a list of epistemic criteria.

Students' interpretation of evidence in relation to claims around complex systems could be directly linked into their model through a "link evidence" button, and their learning of complex systems through representing aspects of the PMC framework in their models were directly scaffolded as pieces for them to create their models (see Figure 1 for a look at all these features). Taken alone, any of these concepts are difficult for students to take on, but we argue here that designing both tools and activities with the integration of these critical scientific practices, help to scaffold students in their complex scientific reasoning. In this particular study, we focus on how this integration led to incredibly rich and detailed interactions around mechanistic reasoning for the students we worked alongside.

Development of mechanisms represented in models of complex systems

In this study, we were interested in focusing on the PMC feature of a causal *mechanism* in order to closely examine how students' mechanistic reasoning was mediated through the use of the MEME tool and designed learning activities. Here, we define *mechanism as* the "entities and activities organized such that they are productive of regular changes from start or setup to finish" of a scientific phenomena (Machamer et al., 2000, p. 3). Within complex systems, mechanisms are the underlying relationships that often go unobserved by novices, and are only made clear when focusing on how various components are interrelated to each other. As a result, mechanistic processes are a common challenge for students when first learning about phenomena (Hmelo-Silver and Azevedo, 2006).

Schwarz and White (2005) outline plausible mechanisms as a key epistemic criterion needed to understand the nature of scientific models. There is a need for students to understand that models consist of causal mechanisms in order to understand their explanatory purposes (Pluta et al., 2011). Our design goals were to engage students in scientific modeling activities which explicitly scaffolded mechanistic explanations to support students in developing their systems thinking and understanding of scientific modeling. In MEME for example, one of the core modeling features

Theoretical Conjectures	Embodiments	Mediating Processes	Outcomes
Integrating *epistemic criteria*, *scientific modeling*, *complex systems thinking*, and *grasp of evidence* into learning scaffolds that will support students' scientific inquiry by helping students: • Focus on students collaboratively developing epistemic criteria for scientific modeling • **Modeling systems with PMC conceptual scaffolds will bridge the practice of modeling and reasoning about complex systems.** • Collaboratively utilizing empirical evidence to construct and refine models will support student groups in understanding evidence and creating models.	**Tools:** • Software scaffolds of students' model creation, refinement, and linkage of evidence. • Designed empirical evidence and scientific reports for students to parse and understand to fit the problem scenario (i.e. fish dying in a local pond) **Activities:** • **Create models of a complex aquatic ecosystem.** • Iteratively refine models in light of new empirical evidence and peer and expert feedback • Gallery walk; students critique peer models and leave comments in MEME.	**Artifacts:** • Students generated models at various points in the implementation. • Students' comments and feedback on peer models. • **Students' direct links of evidence to their models supported by reasoning.** **Observations:** • Meta-epistemic justification of students' critique of peer models and revision of their own models. • **Evidence of reasoning about causal mechanisms of an aquatic ecosystem in students' interactions.** • Reasoning around empirical evidence to directly link evidence to students' modeling practices.	• Increased epistemic cognition around scientific modeling. • Understanding the importance of peer feedback and critique in science. • **Increased understanding of how complex systems behave and function.** • **Increased understanding represented within models of complex systems phenomena following the PMC conceptual framework.** • **Increased grasp of evidence and practice of scientific inquiry.**

FIGURE 2
Conjecture map of our theoretical and embodied conjectures of the larger project. Bolded items are the focus of the present study.

present within the tool is for students to represent processes (i.e., mechanisms) through the form of labeled arrows (see Figure 1) connecting two entities (i.e., components) in a system.[1]

Attending to how students represent mechanisms as they engage in constructing and iterating on a scientific model can help us to better understand how their mechanistic reasoning develops within interaction. For example, Russ et al. (2008) noted that mechanistic reasoning shifts between levels of reasoning tend to occur when students shift from describing the phenomena in a "show-and-tell manner to identifying the entities, activities, and properties of complex systems" within interaction (p. 520). They also noted that lower levels of mechanistic reasoning may act as "building blocks" to lead into higher forms of reasoning (p. 521). Further, prior work indicates that when modeling, students "generate mechanisms using a wide variety of pre-existing ideas" (Ruppert et al., 2019). Looking closely at how students' mechanistic reasoning developed across a modeling unit through the use of various mediators can help us to understand how to better support these practices and provide insight into designing for these kinds of mediating interactions in future iterations of the project.

While the literature emphasizes that domain-specific knowledge can foster the development of mechanistic reasoning in models (Duncan, 2007; Bolger et al., 2012; Eberbach et al., 2021), a key finding in our prior work was "that neither the type nor the number of domain-specific propositions included was important to how students developed mechanisms," (Ruppert et al., 2019, p. 942). These contradictions in the literature indicate a need for further investigation on how students' mechanistic reasoning develops in interaction when engaging in modeling. Researchers are undertaking these kinds of efforts, such as work by Mathayas et al. (2019) utilizing epistemic tools, such as embodied representations of phenomena through gesture, which can support the development of mechanistic explanatory models. We set out with similar goals in this study to investigate how MEME and our designed learning activities can help to support these same shifts in students' representations of mechanism in their modeling.

Methods

Design

The larger project that this study is a part of, SEEDS, aimed to understand how fifth and sixth grade students engage with evidence as they explore complex aquatic ecosystems through modeling. In commitment to our design-based research approach (Cobb et al., 2003; Quintana et al., 2004), we created conjecture maps (Sandoval, 2004; 2014) to outline how we believed our theory was represented in our design in order to achieve our curricular and design goals as we moved through designing the modeling unit (see Figure 2). Conjecture maps are visual representations of design conjectures, which "combines the how and the why, and thus allows the research

1 The names here were substituted based on feedback from students in prior iterations of SEEDS. For instance, In earlier implementations, students remarked even after the unit concluded that they were unclear what a mechanism was, but understood it as a process.

to connect a value (why in terms of purpose) with actions (how in terms of design or procedures) underpinned by arguments (why in terms of scientific knowledge and practical experience)" (Bakker, 2018, p. 49). This framing allows designers to make explicit connections between theoretical commitments and material features of a design. Within the conjecture map, aspects of our design that emerged as the focus of the current study are bolded to indicate the guiding design principles that grounded this analysis.

In the spirit of DBR, we have iterated on the design of the MEME tool across the project's lifespan. For example, based on prior pilot work (Moreland et al., 2020) that revealed that students had a difficult time parsing the PMC framework, we adapted the language of the framework to better accommodate our younger 5th/6th grade participants. In MEME, the tool allows students to create entities (components), processes (mechanisms), and outcomes (results of the phenomena) of the aquatic ecosystem (see Figure 1). Through these kinds of design choices, such as using simple visual elements in how students could construct their model, we were able to directly embed scaffolds for the PMC framework into the tools students utilized when learning how to create and refine their model of a complex system.

We carried out a 7 days modeling unit aimed at teaching the phenomena of eutrophication, or when a body of water receives a high amount of nutrients and creates an algal bloom and takes up all of the dissolved oxygen in the water, creating a dead zone. We took part in roleplaying with students, where a team of scientists we called the Fresh Org tasked the students with trying to figure out and create a model of what was going on in Blue Pond. Students took on the task of solving the problem of why fish were suddenly dying during the summer months in a local aquatic ecosystem. 15/17 consented students were assigned to small groups (2–3 students), and used MEME to develop a comprehensive model to explain what caused the fish to suddenly die in the summertime. On day 1, we introduced the concept of scientific modeling in a short lesson we created based on prior implementations of SEEDS (Danish et al., 2020). We also introduced the activity that students would be tasked with researching the problem and building a model to represent what was going on in the system. From days 1 through 4, students received new evidence sets from Fresh Org related to sunlight, algae, nutrients, dissolved oxygen, the fish in the pond, and water quality related to the system (see Figure 3 for an example of these reports). Each evidence set consisted of 2–3 pieces of empirical data or reports, via the evidence library in MEME (see Figure 1).

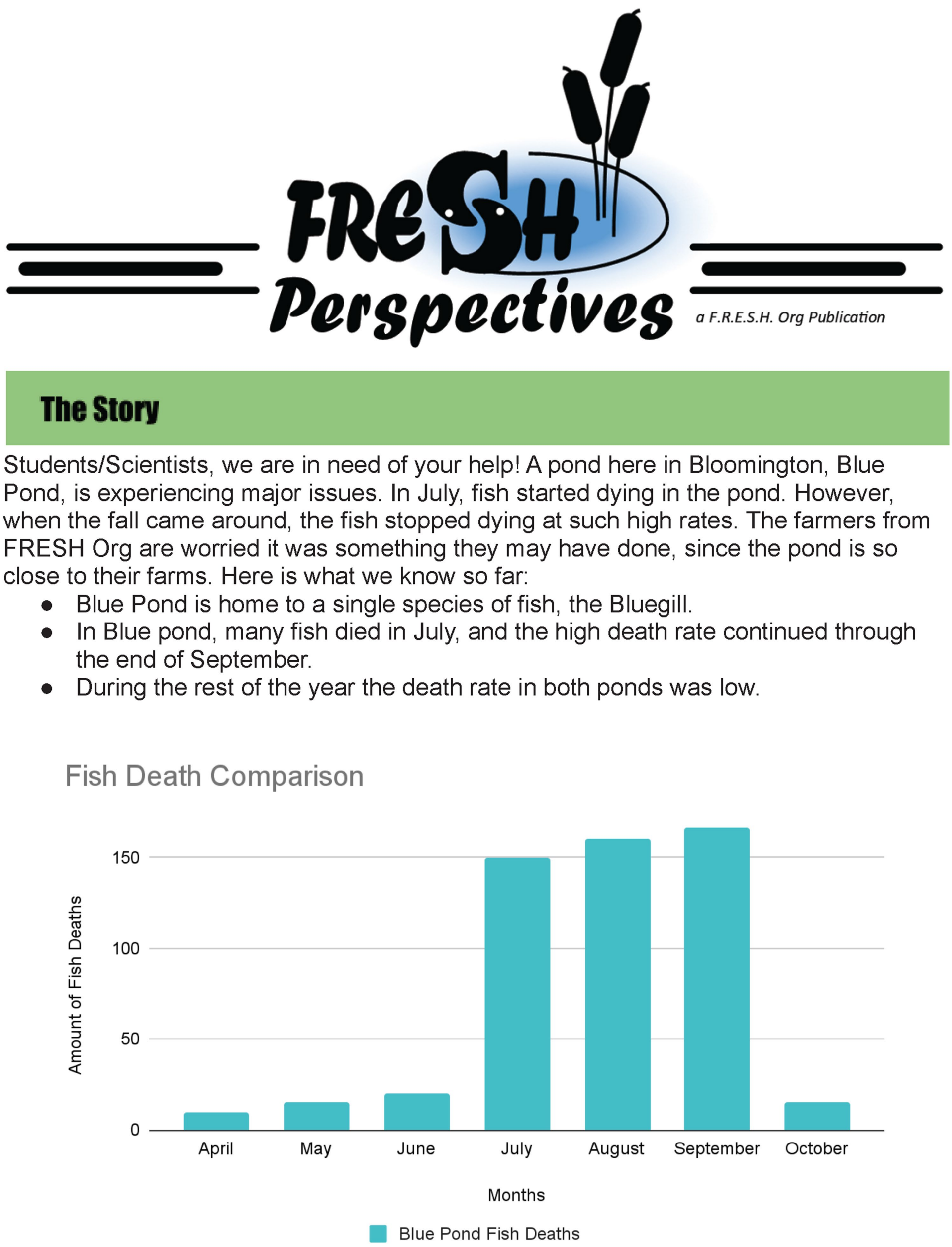
The evidence sets each had a theme (e.g., fish death, algae, fertilizer and nutrients) and disparate pieces of evidence were deliberately paired together for students to connect in their models (e.g., a piece of evidence that had fish deaths highest in the summer, and a farmer's inventory list marking that they distributed pesticides and fertilizer in the month of June). As students interpreted evidence and created their models, facilitators including the research team and the classroom teacher went around the room helping with technical difficulties and asked scaffolded probing and discussion questions (e.g., "do you think this evidence supports anything in your model?"). At the end of each day, students would provide feedback of questions they still had about the complex system, which Fresh Org would then respond to with a summary at the start of each day.

Students collaboratively worked through this evidence in their groups, and then constructed and refined their models in MEME. During days 2 and 4, students participated in a structured "gallery walk" activity where they (1) gave peer feedback on peer models, (2) addressed comments made by peers on their models, and (3) made revisions to their models based on peer feedback. Students finalized their group models on day 5 of the unit, and on day 6 the whole class collaboratively created a consensus model. Finally on day 7 the entire class participated in a discussion of the implementation, where students discussed the epistemic nature of evidence and modeling, along with what caused the initial problem in the pond, the wider effects algal blooms and fertilizer can cause, and the possible solutions on how farmers and community members might prevent these kinds of problems from happening in the first place.

Context and participants

Across the larger DBR project, we have worked closely with multiple teachers in both public and private schools. The context of the present study was a local private school in the Midwestern United States in the fall of 2021, where we had previously worked with the 5th/6th grade teacher of the school on pilot studies of this project. We met with the teacher multiple times in the months leading up to the implementation, where he had direct input into the decisions and designs, such as our empirical reports and evidence, before we began. During the implementation, while the teacher preferred that we run the activities and technology, he was an integral facilitator and supported the activities in the classroom. He often asked discussion questions to students as we wrapped up the day. During modeling activities, he would walk around the room and assist students when creating and revising their models, and during gallery walk activities where students critiqued each other's models he instilled a classroom norm of offering two compliments for every piece of critique offered in someone's model. He also helped to facilitate any whole class discussions that occurred in the class, such as on day 7 when the class had a debrief discussion on the unit.

The research team went in every other day for 4 weeks for a total of 7 days, with a pre-post interview taking place at the beginning and end of the implementation According to our demographics survey we administered, of the 15 consented students who participated in the study, there were 8 girls, 6 boys, and 1 other/unspecified. Researchers taught a designed model-based inquiry unit about eutrophication in an aquatic ecosystem over 7 days, with each day being 90 min long. The unit was created by the research team, which consisted of science education and learning sciences scholars, to align with the NGSS Lead States (2013) standards and core goals, such as cross-cutting concepts. We chose to create this unit from the ground up to align it with the design of our research goals and the MEME software tool. Additionally, we collaborated with the teacher while we designed the unit. He informed us of what his students had learned in his science units already, including how to test water quality and the importance of keeping water within the community's watershed clean. This collaboration allowed us to better integrate the modeling unit to connect with the teacher's existing science curriculum, including the creation of pieces of evidence related to water quality that students used to inform their model construction. Each day of the activity unit took place during the students' science block time in their schedule during regular class time. Students then worked in small groups (6 dyads and 1 triad) in MEME to iteratively build and edit scientific models using a library of designed empirical evidence.



FRESH Perspectives

a F.R.E.S.H. Org Publication

The Story

Students/Scientists, we are in need of your help! A pond here in Bloomington, Blue Pond, is experiencing major issues. In July, fish started dying in the pond. However, when the fall came around, the fish stopped dying at such high rates. The farmers from FRESH Org are worried it was something they may have done, since the pond is so close to their farms. Here is what we know so far:

- Blue Pond is home to a single species of fish, the Bluegill.
- In Blue pond, many fish died in July, and the high death rate continued through the end of September.
- During the rest of the year the death rate in both ponds was low.

FIGURE 3
An example of an empirical report given to students.

Data collection

The primary data source for this analysis was the set of models that students created throughout the project. While students revised their models daily, we focused on their progress through the curriculum unit by examining the models on days 1, 3, and 5 out of the 7 days. These days were chosen because day 1 was the first-time students used MEME to begin constructing their models, day 3 was approximately the mid-point of the implementation, and day 5 was the final day that student groups created their models. On day 6 the class made a consensus model, and day 7 was a debrief with the whole class. A second data source consisted of video and audio recordings of classroom interactions and screen recordings of students building their models in MEME to look into what scaffolds and interactions supported students' systems thinking. Specifically, we were interested in what within student interaction mediated their construction and reasoning around mechanisms of the complex aquatic ecosystem, as well as how their mechanistic reasoning shaped their model construction.

Data analysis

Analysis of this data consisted of qualitatively coding students' models for mechanistic reasoning. This was followed by a close examination of content-logged video data capturing the creation of mechanisms in models, and the interactions between peers which led to their creation. Students' models were qualitatively coded by three researchers focusing on the complexity of students' mechanistic reasoning. We adapted Russ et al. (2008) coding of mechanistic reasoning, which specifies a hierarchy of mechanistic reasoning developments in student interactions (see Table 1). One code from the original codebook, "identifying entities," was removed due to "entities" being one of the embedded features of the MEME modeling tool and thus we wanted to avoid inflating students' code frequencies. While Russ's coding scheme was originally meant for looking directly at student interactions, it has also been used to code student generated models as well (Ruppert et al., 2019). Qualitative coding of models consisted of looking at MEME models at certain points in time in the unit and coding the individual processes and entities within a model as a represented mechanism. For consistency within our data set, a mechanism in a MEME model consisted of two entities connected by a process (see Figure 1 for an example). Each of these were coded within a groups' model, with each group having an average of 3–6 mechanisms per model, depending on the group and day of the unit.

To begin the coding process, we carried out Russ's coding scheme on a subset of models to establish interrater reliability. Following conventions of interrater reliability (McDonald et al., 2019), Author 1 coded the models from the end of day 5 of the implementation (33% of the total data set). The final models from day 5 were initially selected because we anticipated that as the final model, they were likely to be the most complex and complete. Following coding of this subset, two additional members of the research team coded the same set of models. In two separate collaborative coding sessions, the team reviewed the coding and discussed each discrepancy that arose between the researchers. By the end of the two sessions, the coding between the three researchers reached a high degree of interrater agreement (95%). Once agreement was reached on this subset of data, we proceeded to code the remaining models from day 1 and day 3. Once models had been coded for days 1, 3, and 5, Author 1 brought the data set back to the research team to look over the results of the coding, where agreement was once again reached (95%).

Following analysis of students' models, we conducted interaction analysis (IA; Jordan and Henderson, 1995) to closely investigate how students' mechanistic reasoning emerged and developed across the modeling unit. We looked at previously content-logged video data consisting of students' discourse as well as their screen recorded actions carried out on the computer within MEME. The content-logged video data identified specific moments where groups created or revised a mechanism in their MEME model, and marked the interactions occurring during these moments. Different student groups were chosen at random to analyze their interactions each day. The models were analyzed (1, 3, and 5) to report on more general group trends as opposed to the unique developments had by any one group. This way, the interactions analyzed highlighted how the students' engagement with the different mechanisms in the system mediated and in turn were mediated by various features of MEME (e.g., the evidence linking feature) and participating in modeling activities (e.g., taking time to revise their models based on interpretation of new evidence). In these episodes, we looked for elements in MEME and the overall activity which directly influenced students' reasoning about the complex aquatic ecosystem.

Specifically, we unpacked what occurred during group interaction through examining students' talk and corresponding moves made within MEME just before or during the creation of mechanisms in models. We were interested closely examining interactions to better understand the ways in which students discussed and represented mechanisms in ways that might not be clear in simply reviewing the static representation of models. We focused on the reciprocal relationship of the identified mediators: students' interpretation of evidence, features of MEME linking evidence to their models, their negotiations surrounding mechanisms, and their modeling practices. By reciprocal relationship, we mean that each mediator shaped students' participation in the activities and how they took up other mediators present to support students' learning throughout the unit. For instance, while students' interpretation of evidence mediated how students' represented mechanisms in their models, their mechanistic reasoning in turn mediated how they read through and interpreted the sets of evidence. The IA we conducted revealed how features of MEME and interaction around the creation and revision of their model transformed their mechanistic reasoning, but also how students' focus on mechanisms within the complex system shaped the way they used MEME and developed their epistemic criteria of what

TABLE 1 List of codes used for student models.

Mechanistic reasoning code	Description	Examples from student models
1. Describing target phenomena	When students clearly state or demonstrate the particular phenomenon or result they are trying to explain.	[Within a description of a created entity "Fish"] – *"Fish are dying in the pond that is near the farm"*
2. Identifying setup conditions	Moments when students identify particular enabling conditions of the environment that allow the mechanism to run.	[Process in MEME] – *"Fish start to die ➔ new season ➔ less algae"*
3. Identifying activities	When students who articulate the actions and interactions that occur among entities.	[Process in MEME] – "*pesticides ➔ spreads to ➔ lake/pond*"
4. Identifying properties of entities	When students articulate general properties of entities that are necessary for this particular mechanism to run.	[Entity in MEME] – "*Farmers like [pesticides] because it kills bugs*"
5. Identifying organization of entities	When students attend to how the entities are spatially organized, where they are located, and how they are structured.	[Process in MEME] – "*Fish ➔ fish are in the blue pond ➔ Blue pond*"
6. Chaining: Backward and forward	We observe students reasoning about one stage in a mechanism based on what is known about other stages of that particular mechanism and code this type of reasoning as "chaining."	[Processes in MEME] – "*Algae ➔ lowers ➔ Low dissolved oxygen ➔ suffocates fish ➔ dead fish*

makes a good model. We unpack the results of both the coding and the interaction analysis in the results below.

Results

Russ et al. (2008) hierarchy (see Table 1) of students' mechanistic reasoning was based on what they determined to be more or less scientifically sophisticated. We took up that same hierarchy based on our prior work of adapting this coding scheme from interaction to student generated models (Ruppert et al., 2019). Our analysis of student models showed a general trend that the mechanisms represented across all group models became more complex as the unit continued (see Figure 4). Interaction analysis carried out on students' interactions surrounding the creation of these mechanisms revealed several distinct mediators which promoted the creation or refinement of mechanisms in their group models. These include interpreting disparate forms of data in order to make claims identifying mechanisms, utilizing and linking evidence to help develop and refine their mechanistic reasoning, and how playful peer interactions helped to shape their reasoning around mechanisms.

Development of mechanistic reasoning across time

Students' coded models clearly exhibited development in complex mechanistic reasoning as students iterated on their models of the aquatic ecosystem (see Table 2). Collectively, the development of mechanisms across student models across time improved from the end of day 1 to the end of day 5 (when student models were finalized), with high level mechanisms (levels 4–6 in our coding scheme) being present in all student groups' models starting at the end of day 3. Not only do our results indicate that students identified and represented more mechanisms within the system as the unit went on, but the majority of mechanisms coded across all final models at the end of day 5 were coded on the upper half of the Russ's coding scheme for mechanistic reasoning (54% of all mechanisms across all group models). This distribution was evenly spread across groups, with 7 out

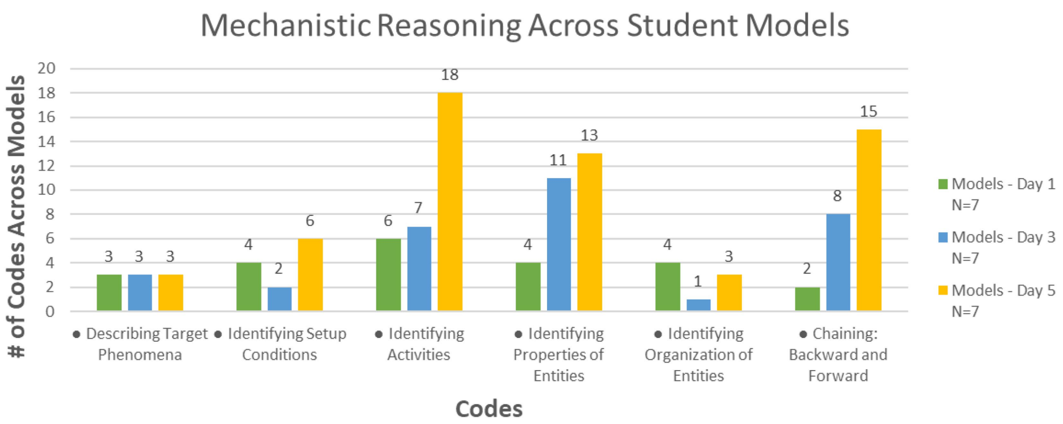


FIGURE 4
Bar chart of total codes for each day of models.

TABLE 2 Results of qualitative coding of student models.

		Models – day 1 (n =7)	Models – day 3 (n =7)	Models – day 5 (n =7)	Totals (n =21)
Mechanistic reasoning	Describing target phenomena	3	3	3	**9**
	Identifying setup conditions	4	2	6	**12**
	Identifying activities	6	7	18	**31**
	Identifying properties of entities	4	11	13	**28**
	Identifying organization of entities	4	1	3	**8**
	Chaining: backward and forward	2	8	15	**25**
	Total codes	**23**	**32**	**58**	**113**

Bold values denote the totals for each row and column.

of 7 of the groups representing at least one high level mechanism within their final models.

These results are a clear indication that students were using MEME to represent sophisticated mechanisms of the complex system, as seen in the increase in higher coded mechanisms across all models as the unit progressed (see Figure 4). Even lower coded parts of the model, such as *describing target phenomena,* and *identifying setup conditions* indicate that students were reasoning about causal mechanisms within the system, which are critical for students to understand if they are to effectively learn about both modeling practices (Pluta et al., 2011) and complex systems thinking (Goldstone and Wilensky, 2008). This meant regardless of complexity, students were making causal connections to each and every component of the system that they chose to represent in their modeling. This highlighted that students represented what they interpreted as key aspects of complex systems as they carried out their scientific inquiry.

Furthermore, the majority of all mechanisms that emerged across models were in the middle of the hierarchy and higher, going all the way up to the highest code of chaining together causal chains of various mechanisms to explain how the aquatic ecosystem functions. The three most common coded mechanisms that emerged in students' models were: *identifying activities* (level 3; 27% of mechanisms), *identifying properties of entities* (level 4; 25% of mechanisms), and *chaining* (level 6; 22% of mechanisms), accounting for 74% of all mechanisms present across student models. Two out of three of the most common codes were in the top levels of Russ's coding scheme, with only one high level code not commonly occurring across student models in high volume, *identifying organization of entities* (level 5, 7% of mechanisms). However, in total 7 out of the 7 final models had >50% of their mechanisms coded as the top half of mechanistic reasoning codes. These percentages represent the distribution of mechanisms across all student models on days 1, 3, and 5, which were consistent across individual models as well.

Student models ranged from having between 3–10 mechanisms present in their model depending on the day and group, but distributions of codes were evenly spread across groups. Table 2 highlighted that the three most complex forms of mechanistic reasoning were the majority of coded mechanisms across all models (54% of all coded mechanisms). As we move across each selected day of modeling, we can see a clear development of mechanistic reasoning happening for student groups. The total number of mechanisms identified increase as we move from day 1 to day 3 to day 5 (see Figure 4), which indicated that student groups added more elements to their model in total. We also see a distinct shift in how many complex types of mechanistic reasoning begin to emerge in students' models. Specifically, *identifying activities*, *identifying properties of entities*, and *chaining* appear at much higher volumes in models as we move across time in the implementation. Figure 4 provides a bar chart visualizing the distribution of coded mechanisms at the conclusion of days 1, 3, and 5 of the unit.

Students' development of mechanistic reasoning as time went on can be seen most clearly in the development of students' use of causal chaining in their models, or when students reason about one stage in a mechanism based on what is known about other stages of that particular mechanism (see Figure 4). For instance, at the end of day 1 few groups had used any sort of chaining to represent how components of the aquatic ecosystem were related (8% of coded mechanisms). However, at the end of day 5, when students finalized their models of the aquatic ecosystem, chaining causal mechanisms was the second most occurring code across student models (26% of coded mechanism). Breaking this down by group, 5 out of 7 groups had more than one mechanism coded as chaining in their models, and 7 out of 7 groups each had between 2–4 mechanisms coded in the top half of Russ's coding scheme. Students' development in their mechanistic reasoning can clearly be seen across time as they iterate and refine their models.

Mediating the creation of mechanisms within models

Analysis of student interactions around the creation of mechanisms highlighted the key role of the features of MEME, including the evidence resources that students were investigating. These directly mediated students' talk within their groups surrounding the creation of mechanisms in their models. Below, we analyze episodes of interaction at moments where students created mechanisms within MEME during days 1, 3, and 5 of creating and refining their models of aquatic ecosystems.

Interpreting disparate evidence in the construction of mechanisms

At the start of day 1, students only had access to two pieces of evidence to support their model creation. This was intentional, as this was students' first-time using MEME, and they were working to understand the primary features of MEME including creating new components and mechanisms to represent the system through their modeling. Students were just starting out and trying to represent and explain the initial problem they had been given – that fish were dying in the pond during the summer months. The first piece of evidence introduced the problem, and provided a graph showing what months the fish deaths rose (July–September). The second piece of evidence was a list of materials used by farmers in nearby local farms, which included pesticides and fertilizer which were distributed in June. Students were tasked with reading these two separate pieces of evidence and creating an initial model.

Students were new to MEME and scientific modeling in general, and were given the task of creating a few entities and processes of the phenomena they were just introduced to. While the mechanisms across groups began as fairly straightforward at the end of day 1 (see Table 2), student interaction revealed the nuanced interactions surrounding the creation of students' first mechanisms within their models. For example, a group with two students created their first four processes to represent the possible causal mechanisms of farms spreading pesticides into the pond, which then kill the fish. Students had just reviewed the farmer's inventory list in the evidence library, and like many other groups gravitated towards the use of pesticides in the farm. While pesticides were merely a part of the inventory list, they were not framed in any particular way in the data. For instance, in an exchange with a facilitator, Eddy and Lily explained why they connected the two pieces of evidence to construct their first causal mechanism (see Figure 5).

When the facilitator initially called their attention to the inventory list, Eddy noted that fertilizers and pesticides could be harmful because they were distributed to the local farms in the month of June (lines 2–3). The facilitator inquired how they knew this, and Lily

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Speaker	Line	Dialogue	Moves made in MEME
Facilitator	1	*So this table is important, there's some information there.*	
Eddy	2	*Yeah the fertilizers and pesticides, it says the pesticides were used in*	Eddy and Lily looked through and highlighted fertilizer and pesticides in the inventory list
	3	*June, and fertilizers could have bad stuff, and also pesticides can.*	
Facilitator	4	*Oh interesting, so how did you get that?*	
Eddy	5	*Because it says its in June, and the fish deaths started happening in*	Eddy connected the two pieces of evidence together, and stated that fertilizers and pesticides were spread around the time the fish died
	6	*July, and um it like, it um -*	
Lily	7	*- Because this has the most… July August September*	Lily navigated to the first piece of evidence and explains that the graph of fish deaths are right after the pesticides got distributed.
Eddy	8	*Yeah*	
Lily	9	*But the pesticides take awhile to go in, so you can see it goes up and*	
	10	*up and up and up more and then a straight stop.*	

FIGURE 5
Transcript of Eddy and Lily's initial claim that they added to their model.

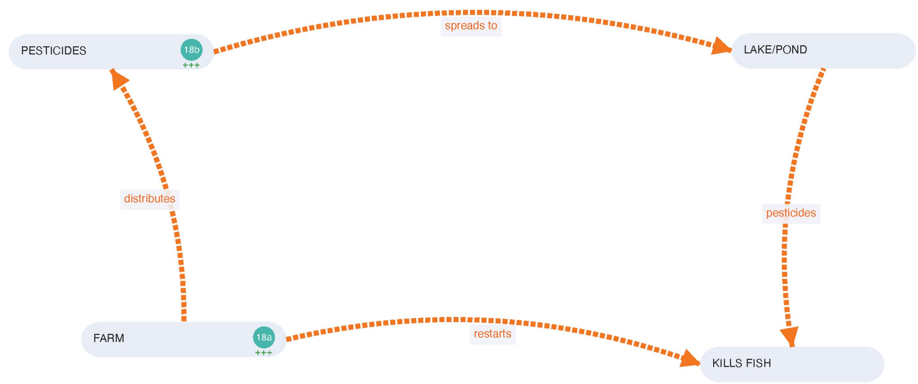

FIGURE 6
Eddy and Lily's model at the end of day 1.

navigated to the first piece of evidence in MEME, pointed the computer mouse to the graph and pointed out that fish deaths were the most in the summer months (line 7). She then made a claim that the pesticides likely took a while to get to the water, and "so you can see it goes up and up and up and up more and then a straight stop" (lines 9–10). Eddy and Lily interpreted separate pieces of evidence, and integrated them into their initial claim represented in their model of the complex systems.

They chose to only represent pesticides (possibly because of prior knowledge surrounding mainstream debates around pesticide use), but reasoned that the farm distributes pesticides, which then spread to the pond, and so the pesticides kill the fish, which then restarted the process. Figure 6 shows how their representation of this mechanism was represented across multiple entities and processes within their model.

What stopped these mechanisms from being coded at higher levels, such as chaining, was that they were isolated in how they were represented, as opposed to being informed by other mechanisms of the system. Given that this instance was at the start of the unit, this makes sense, and the interaction above marked a promising start given their sophisticated interpretation of evidence. The overall trends of mechanism codes at the end of day 1 indicate that Eddy and Lily's model was typical of what other student groups created as well (see Table 2). This meant that students had a similar interpretation of the two disparate pieces of evidence to reason about the causal mechanisms of the system.

Within these interactions, students analyzed and interpreted novel and distinct forms of data, interpreted connections between them in order to make an initial claim, and then represented their claims through a series of causal mechanisms within their PMC model. Eddy and Lily's grasp of evidence here, specifically their interpretation and integration of evidence, mediated the ways in which they chose to represent their initial constructions of their model. Their integration of disparate evidence directly supported the claims that they represented through their mechanisms within their model.

Negotiating and linking evidence in the model

During days 2 and 3, students had their first opportunity to offer peer feedback through a "gallery walk" activity where students went into each other's models in MEME and commented how well they thought it represented the problem they were trying to solve (see Figure 1 for how this feature looked in MEME). They then were able to revise and refine their models based on that feedback. They also examined new sets of evidence that might help them to solve the problem of why fish were dying in the pond. This led to students iteratively improving their representation of mechanisms in their model in response to peer critiques, which we detail in an example below.

The distributions of coded mechanisms within models (see Figure 4 or Table 2) revealed that at the end of day 3 students were using MEME to represent more complex forms of causal mechanisms in their model. This occurred primarily by more explicitly naming the process that caused the mechanism between two components of the system. Our IA during this point of the implementation revealed that all student groups were collaboratively reasoning around causal mechanisms of the system to negotiate revisions and changes made to their model. For example, two students in a group, Jenny and Claire, made several revisions of both components and mechanisms within their MEME models (see Figure 7).

In one instance, upon receiving peer feedback in the form of a comment which read "it's a great model but I think you should be more specific," the group revised a specific entity and process to better represent the causal mechanism of the system. They modified an existing entity which originally read "More Oxygen" and revised it so that the entity was "Less Algae" and added "More Dissolved Oxygen" to the existing process "less death." This may not seem significant, but it marked a shift in their mechanistic reasoning represented in their models (along with 5 out of 7 of the total groups). Based the feedback and new data that Jenny and Claire had just read, they modified the claim that less algae present in the pond was the main reason that there was more dissolved oxygen in the water and less fish death at the start of a new season. This was Jenny and Claire's first mechanism that was coded as *Chaining*, the highest code for mechanistic reasoning present within the models. In changing one of their mechanisms from "new season ➔ less death ➔ fish" to "less algae ➔ more dissolved oxygen and less death ➔ fish lay eggs," they began to chain together their reasoning across mechanisms (see Figure 7). What's more, however, is that their further interactions when deciding to link a piece of evidence reveal further insight to how they worked towards representing their claims surrounding this particular mechanism of the system, that less algae in the water provided more oxygen and therefore less fish death (see Figure 8).

In this exchange, Claire and Jenny negotiated how to provide reasoning behind choosing to link a piece of evidence, a report on how much algae grew in the pond over the course of 6 months, in support of one of their claims represented in their model. Claire narrated her thoughts to Jenny, who typed for her. Jenny misunderstood Claire's explanation during this exchange and typed an incorrect claim (that there were less algae at the same time the fish die). Claire noticed this and called this out by correcting Jenny and says "The algae is lower at the same time the fish die? [but] death is low! (lines 16–17). Jenny recognized this and corrected it quickly, but let Claire know that explanation was not what she had in her own mind (lines 18–19). Claire remarked that it still worked however, and the pair were left satisfied by their linked evidence.

Their conclusion in linking their evidence was that "Because the algae is lower the same time that the fish death is lower." They linked this to the process in their model to support their mechanism which claimed that less algae meant more dissolved and less fish death. Two distinct mediators emerged which supported students' mechanistic reasoning here for Claire and Jenny. The first is the act of revising their models upon receiving peer feedback. Peer feedback within their model led them to revisit evidence and negotiate how to better represent their mechanism. This supported them in making revisions to their model. These changes to existing features of their model led to higher coded mechanistic reasoning represented in their model, as evidenced by the emergence of 2 distinct instances of mechanisms coded as *chaining* to this group's model at the end of day 3.

Second, MEME's link evidence feature, which allowed for students to directly link their evidence interpretations into their models, supported further interactions and reasoning on how to explain their claims. The interaction above highlighted how the feature in turn supported negotiation on how Claire and Jenny represented their claims and led to a deeper collaborative understanding of their collective reasoning. The evidence link feature has a prompt which asks students to draw a conclusion from the connection they made to their model (see Figure 1 for an

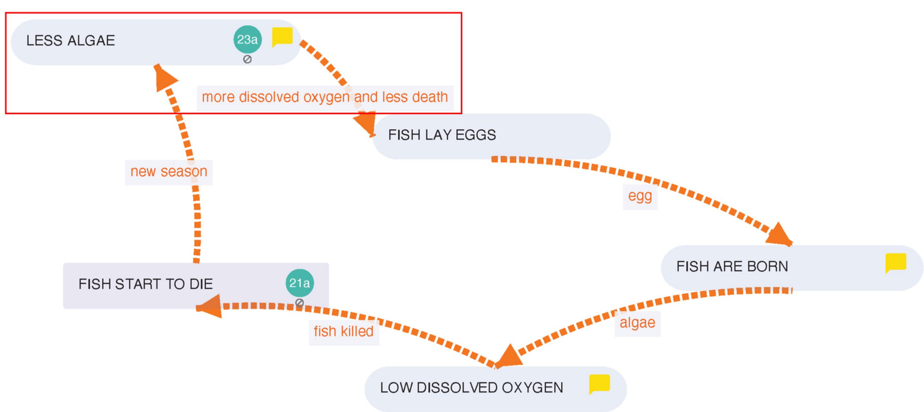

FIGURE 7
Jenny and Claire's model on day 3 of the modeling unit with changes highlighted.

Speaker	Line	Dialogue	Moves made in MEME
Facilitator	1	*Okay, you need to click edit, so now you can choose*	
	2	*select target*	
Claire	3	*Al-algae*	
Facilitator	4	*Okay so now click there, and that should do it.*	
Claire	5	*Less algae*	
Facilitator	6	*There you go, now its all linked. Now say why. So put*	Upon receiving feedback, Claire attempted to directly link a piece of evidence to her model.
	7	*the conclusion there um and update that, and then you*	
	8	*can close it when you're done.*	
Jenny	9	*Do I have to type more? Okay what do you want me to*	
	10	*type? What?*	
Claire	11	*Because…the…algae…is…lower…that the same time…*	Jenny and Claire discussed how they wanted to describe their evidence link into the model in order to justify the claim they made in a new mechanism they created during revision.
	12	*the death is lower…*	
Jenny	13	[Typing]	
Claire	14	*Death! I said death not dying…you're not finished*	
Jenny	15	[Typing]	
Claire	16	*The algae is lower at the same time the fish die?*	
	17	*…death is low*	
Jenny	18	*I guess this won't make as much sense as what I had in*	Claire and Jenny negotiated how to frame their reasoning around linking their evidence to support their model.
	19	*mind.*	
Claire	20	*But it still works!*	

FIGURE 8
Transcript of Jenny and Claire revising their model to improve their mechanisms.

example of this). Jenny and Clair spent time negotiating on how to frame this conclusion, eventually coming to an agreement about how they should frame their reasoning (lines 16–20). This negotiation around how to frame their conclusion led to a collaborative understanding of how Jenny and Claire represented their claims within their models.

Mechanistic reasoning through creative modeling practices

On day 5 out of 7 of the unit, students received their final set of evidence, which informed them that nutrients within fertilizer helped to promote plant growth, and that the algal bloom coincided with a heavy rainfall. Here, two modeling trends began to stick out to us as we moved through the data, all of which stemmed from students using the MEME tool to represent their thinking around the complex system in novel ways. First, students began to create parts of their model to note aspects of the complex system that they did not currently have a full explanation for. For instance, in one group Ben and Henry created two processes related to algae and dissolved oxygen to mark that they thought there was a relationship between the two, but were unsure of what the specific relationship was, a practice which we encouraged to help drive conversations about how to support and clarify such claims (see Figure 9).

Ben and Henry elected to create two processes, "Low Dissolved Oxygen → idk (i.e., I do not know) algae dies or something → High Dissolved Oxygen," and "High Dissolved Oxygen → idk algae grows or something → Algae." They noted the relationship between algae and dissolved oxygen, but could not yet support their claims with evidence. These ended up being coded on the lower end of the coding scheme. Their other mechanisms, which were more detailed and coded higher in their models, were all directly linked to pieces of evidence (see Figure 9). Here, Ben and Henry not only represented their model as something that could be revised as they learned more, but also that the mechanisms they were confident in were directly supported by their grasp of the evidence available to them through directly linking evidence to parts of the model they were sure of (see Figure 9). This lined up with how their model at the end of day 5 was coded, with their two highest coded mechanisms of chaining being connected to the parts of their model directly supported by evidence. This is noteworthy because it indicated that even their lower coded mechanistic reasoning present in their models did not necessarily represent a lack of understanding on their part, but rather coincided with modeling practices which noted parts of their model as a work in progress which needed refinement.

Second, many groups began to engage in playful inside jokes and goofing around and tapped into what Gutierrez et al. (1995) call the underlife of the classroom, where students "work around the institution to assert their difference from an assigned role" (p. 451). As Gutierrez and colleagues point out though, this is not inherently unproductive or off-task behavior, and can be mediated through interaction to be powerful moments of learning. For instance, upon looking over evidence that showed that one fish died from a turtle attack while the others suffocated from low oxygen levels, Ben and Henry decided to add the turtle to their model as an entity.

When this turtle emerged in their model alongside a process labeled "lol" (see Figure 10), Ben and Henry decided that they

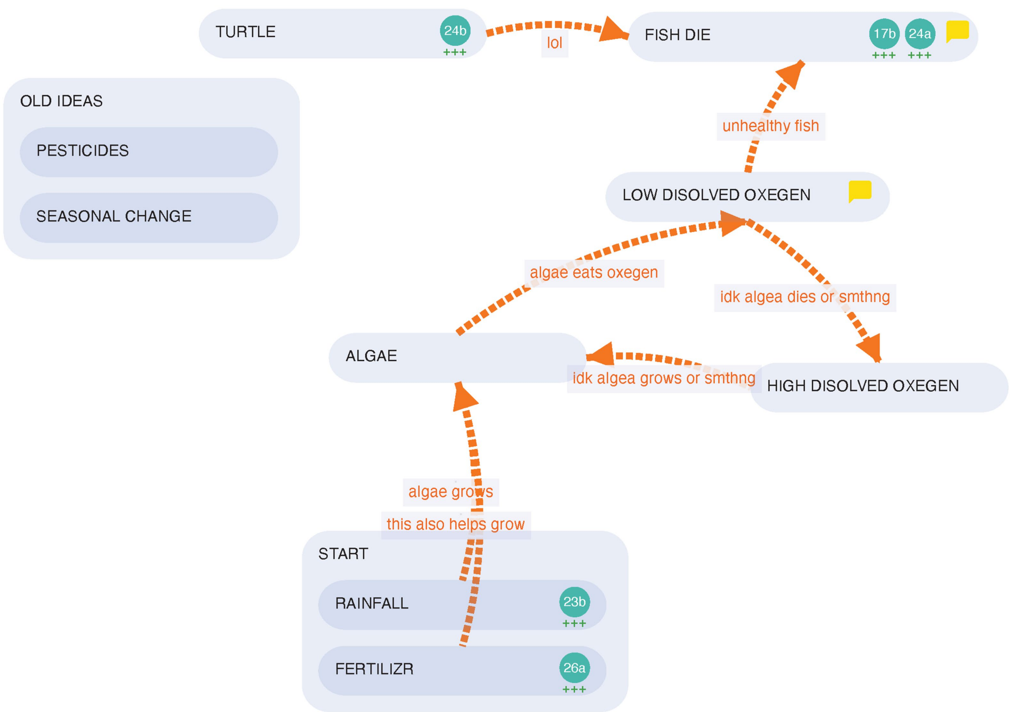

FIGURE 9
Ben and Henry's model at the end of day 5.

Speaker	Line	Dialogue	Moves made in MEME
Ben	1	*We're gonna add [an entity] to the side that's just called turtle*	Ben and Henry created a joke entity of turtle, connecting it to fish death through a "lol" mechanism.
Henry	2	*Now add it!* [Laughter]	
Ben	3	*Well we're just keeping it true to the autopsy report* [laughing]	
Henry	4	*Make [the process] lol* [laughter]	
Ben	5	*Okay we did it, we edited because of the thing we added turtle!* [Laughter]	Ben showed the turtle entity to a facilitator, who asked a few probing questions to clarify if this was their new theory. Ben clarified that, no, they just put it in for fun, and the same evidence proved their original suffocation theory.
Facilitator	6	*So, do you think that turtles were the primary cause of fish death?*	
Ben	7	*No! That's why we added it to the side cause one of them killed them*	
Facilitator	8	*Fish, turtle, lol... okay. Alright, did you learn anything else from it?*	
Henry	9	*No!*	
Ben	10	*Well, we learned that they did suffocate and it proves our theory*	
Henry	11	*Oh wait yeah!*	
Ben	12	*But the turtle killed him, but he was already going to suffocate anyways because it*	Ben made an important note in the evidence that even though one fish died from a turtle, it *also* had low blood oxygen.
	13	*also had low blood oxygen levels so the turtle just like killed it early!*	

FIGURE 10
Screenshot and transcript of Ben and Henry reading over a piece of evidence.

needed to show this off to a facilitator. They showed the turtle to a facilitator, who proceeded to ask if this was now their primary theory of how the fish died. Ben remarked that "No! That's why we added it to the side cause one of them killed them" (line 7). Ben then proceeded to inform the facilitator that the evidence they had learned about the turtle also confirmed their original claim that the fish had suffocated in the water due to low oxygen (line 10). Ben went on to further explain that "the turtle killed him, but he was already going to suffocate anyways because it also had low blood oxygen levels so the turtle just killed it early" (lines 12–13). Despite their fixation on the turtle, their interaction around it revealed a deep understanding of what was happening within the system on an unseen level, that fish were suffocating because of a lack of oxygen due to the algal bloom.

This particular interaction was important for us to unpack because without the rich interactional context, the static mechanism of "Turtle → lol → Fish Die" may appear to be off-task behavior or even an incorrect interpretation of the evidence and their model. Ben and Henry noted their clear interpretation of the evidence within their discourse with each other and the facilitator, which further supported already created mechanisms in their model, which they later linked with evidence to further support their claim. Ben and Henry's interaction also highlights how levity and playfulness can lead to deeply nuanced reasoning around the causal mechanisms of a complex system. The underlife of the classroom, such as the inside jokes, silly remarks, or adding funny additions to a sophisticated scientific model further mediated and deepened students' understandings of complex systems and their epistemic ideas of what a scientific model should consist of.

Discussion

This study contributes to larger discussions of how to better integrate ideas of teaching both scientific modeling and complex systems thinking in elementary students' scientific inquiry. We closely investigated how students' mechanistic reasoning progressed and developed while participating in a scientific modeling curriculum unit which was scaffolded with the PMC conceptual framework for systems thinking (Hmelo-Silver et al., 2017a). Our goals of this study were to closely analyze how our various design frameworks, including sociocultural theories of learning (Vygotsky, 1978), mediation (Wertsch, 2017), epistemic criteria (Murphy et al., 2021), grasp of evidence (Duncan et al., 2018), and mechanistic reasoning (Russ et al., 2008) were taken up by our research team and collaborating teacher to better integrate concepts of complex systems thinking (Wilensky and Resnick, 1999; Hmelo-Silver and Azevedo, 2006) and scientific modeling (Pierson et al., 2017) in teaching upper elementary students the nature of science. We sought to deeply understand how our designed activities within a model-based software tool, scaffolded with the PMC framework, support the integration of complex systems thinking and the practice of scientific modeling for elementary students.

The MEME software tool that students used to construct their models directly embodied the core elements of the PMC framework (i.e., outcomes, processes, and entities) as the building blocks in which students constructed their models, as well as making the use of evidence to revise a model salient to learners. Additionally, MEME and the designed modeling unit emphasized constant revision and iteration on student models in light of new evidence given to students surrounding the phenomena they investigated. Initially, students had middling to low levels of mechanistic reasoning emerge in their models, which is to be expected. As students progressed, their reasoning began to improve, and more sophisticated mechanisms began to emerge both in their models and in their peer interactions. By the end, students had a higher number of total mechanisms present in their models, and the majority of coded mechanisms in student models were in the top half of Russ's mechanistic reasoning learning progression (52% of coded mechanisms across models).

Overall, the findings of this study demonstrated that not only were students able to improve their representations of causal mechanisms in these models over the course of the implementation, but that this type of sophisticated reasoning was mediated in students' interactions in a number of ways across the implementation. These mediators included (1) the designed materials such as the empirical reports and data structuring students' inquiry, (2) features of MEME such as the PMC representation, evidence library and evidence linking features, and (3) students' diverse and playful interactions with their peers which provided constant feedback and opportunities to negotiate meaning of parts of their models.

Limitations

There were several limitations of this study. First, while the overall project collected data at a number of diverse sites and contexts, the data for this study was collected at a private school with much more flexibility in curriculum and structure of students' day than a typical public school. The school had a free form curriculum that was in complete control of the teachers, which made it easier for us to collaborate with and integrate our unit alongside our partner teacher. While we have run implementations of the SEEDS project in public school contexts, we had also previously worked with this teacher before, so these specific findings may not be generalizable to school settings with more rigid schedules and curriculum without further investigation. Second, students were creating a very specific kind of model within MEME, and it is difficult to say whether or not a similar result of the development of mechanistic reasoning may emerge when students engage in different kinds of modeling, such as agent-based simulations (Wilensky and Resnick, 1999) or embodied models (Danish, 2014). Finally, the population of students we worked with, along with the identities of researchers, were fairly homogenous and is likely reflected in the ways in which we interacted with students, the materials we designed, and the models that were created during this implementation. Further work is needed to investigate these findings in more heterogeneous spaces, to see what possibilities students have to contribute as they develop their own mechanistic reasoning in new contexts.

Future directions

These findings contribute to ongoing research by demonstrating the effectiveness of bridging together aspects of scientific modeling and systems thinking concepts to teaching scientific inquiry to elementary students. It highlights the effectiveness of embedding aspects of systems thinking directly into modeling tools and curriculum to support students reasoning around complex systems, particularly in relation to students' understanding of underlying and emergent relationships within systems. The results of this study support prior research that demonstrated students' mechanistic reasoning developing on a similar trajectory (Ryan et al., 2021), and extend prior work in analyzing students' development of mechanistic reasoning (Ruppert et al., 2019).

Overall, across the modeling unit students participated in, it was evident that within their interactions with both peers and facilitators, students developed competencies in their reasoning around the causal mechanisms of complex systems, the epistemic criteria that made up a scientific model, and interpreting data to develop their understanding and represent their claims within their model. What's more, students' interactions revealed how intimately connected these aspects of their scientific inquiry were. Their reasoning around mechanisms of the complex system was directly influenced by their interpretations of evidence, which in turn influenced their modeling practices to focus more explicitly on refinement and iteration rather than a single, static representation of the complex system.

Further investigation into how researchers and practitioners can scaffold systems thinking frameworks, such as the PMC framework (Hmelo-Silver et al., 2017b), into modeling tools, curricula, and activities which focus on developing students' epistemic criteria of models (Pluta et al., 2011), and their grasp of evidence (Duncan et al., 2018), can help to improve the bridge between these two core pieces of scientific inquiry. We continue to work to more developed more nuanced understandings of how our designs mediate students' developing understanding of both modeling and complex systems, and hope that this study can offer researchers pursuing similar kinds of work design focal points which may further help to bridge these essential processes of scientific inquiry.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving human participants were reviewed and approved by Indiana University Bloomington Internal Review Board. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

ZR led the majority of research, analysis, and writing on this project. JD helped substantially with research and revisions to the analysis process. JZ and CS helped substantially with interrater reliability and analysis. DM helped with initial designs of the larger project. JD, RD, CC, and CH-S are Co-PIs on the larger projects. ZR, JD, JZ, CS, DM, RD, CC, and CH-S helped substantially with revisions and feedback to drafts of this manuscript. All authors contributed to the article and approved the submitted version.

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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.

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EDITED BY
Orit Ben Zvi Assaraf,
Ben-Gurion University of the Negev, Israel

REVIEWED BY
Carola Garrecht,
University of Kiel, Germany
Daner Sun,
The Education University of Hong Kong, Hong Kong SAR, China

*CORRESPONDENCE
Troy D. Sadler
✉ tsadler@unc.edu

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Exploring system dynamics of complex societal issues through socio-scientific models

Li Ke[1], Eric Kirk[2], Rebecca Lesnefsky[2] and Troy D. Sadler[2]*

[1]College of Education and Human Development, University of Nevada, Reno, NV, United States,
[2]University of North Carolina at Chapel Hill, Chapel Hill, NC, United States

Research on socio-scientific issues (SSI) has revealed that it is critical for learners to develop a systematic understanding of the underlying issue. In this paper, we explore how modeling can facilitate students' systems thinking in the context of SSI. Building on evidence from prior research in promoting systems thinking skills through modeling in scientific contexts, we hypothesize that a similar modeling approach could effectively foster students' systematic understanding of complex societal issues. In particular, we investigate the affordances of socio-scientific models in promoting students' systems thinking in the context of COVID-19. We examine learners' experiences and reflections concerning three unique epistemic features of socio-scientific models, (1) knowledge representation, (2) knowledge justification, and (3) systems thinking. The findings of this study demonstrate that, due to the epistemic differences from traditional scientific modeling approach, engaging learners in developing socio-scientific models presents unique opportunities and challenges for SSI teaching and learning. It provides evidence that, socio-scientific models can serve as not only an effective but also an equitable tool for addressing this issue.

KEYWORDS

socio-scientific issues (SSI), modeling, systems thinking, epistemology, science education

Introduction

In the 21st century, we are confronted with a myriad of complex societal issues such as climate change that are multifaceted and lack universally agreed-upon solutions. These issues not only impact our day-to-day lives but also have long-lasting effects on the environment and society. As educators, we need to prepare future generations to navigate and respond to these complex issues as responsible citizens (De Boer, 2000). Ideally, students should develop the skills necessary to critically evaluate scientific information, understand the social and ethical implications of scientific advancements, and engage in informed decision-making. However, science standards worldwide often fall short in promoting or achieving the full measure of these aims (Feinstein and Kirchgasler, 2015). A primary focus on canonical scientific knowledge and practices fails to address the need for learners to grapple with the real-world complexities that accompany complex societal issues.

Over the past two decades, researchers have explored socio-scientific issues (SSI), complex societal issues with connections to science knowledge, as meaningful learning contexts to promote scientific literacy (Sadler, 2009). Research on SSI has revealed that a significant challenge for learners is to appreciate the complexity of the systems associated with these issues (Sadler et al., 2007; Zeidler, 2014). It is essential for learners to develop a systematic understanding of the issue, considering both scientific and social dimensions (e.g., cultural, political, economic, and ethical factors) and the system dynamics within and between dimensions for informed decision-making (Ke et al., 2021).

The notion of systems thinking is not new to science education (Yoon et al., 2018). Systems thinking entails the ability to recognize patterns, interconnections, and feedback loops within complex systems, as well as the capacity to predict how alterations in one part of the system might impact the whole (Hmelo et al., 2000). Systems thinking is an important skill in STEM education that learners need to master to engage in scientific and engineering practices (Yoon, 2008). Prior research has found that engaging students in modeling practice can promote their systems thinking skills (Stratford et al., 1998; Hmelo-Silver et al., 2007; Dickes and Sengupta, 2013; Nguyen and Santagata, 2021). By engaging students in the creation, revision, and manipulation of models representing complex natural systems, they are expected to develop an understanding of the underlying structure and dynamics of the system through examination of the relationships and interactions among various components (Bielik et al., 2022).

It is important to note that prior research on system models has predominantly focused on exploring systems thinking within the context of science disciplines. Nevertheless, there are significant differences between systems from a science perspective and those involving social components. Therefore, it is critical to consider unique attributes of systems that involve science and social dimensions when teaching systems thinking in the context of SSI, as they differ markedly from systems exclusively defined by science.

In this paper, we explore how modeling can facilitate students' systems thinking about complex societal issues. Building on evidence from prior research in promoting systems thinking skills through modeling in scientific contexts, we hypothesize that a similar modeling approach could effectively foster students' systematic understanding of complex societal issues. In our previous work, we introduced socio-scientific models that incorporates social factors and address the learning needs of students making sense of SSI (Ke et al., 2021). Here, we advance this work and further investigate the affordances of socio-scientific models in promoting students' systems thinking in the context of SSI. Specifically, we examine learners' experiences and reflections concerning the unique features of socio-scientific models that distinguish them from scientific models.

From the outset, we aim to clarify the terms used in this paper related to model categorization, given the lack of consensus in the field. A model can be classified into various types depending on the criteria used. For instance, a NetLogo (Wilensky, 1999) simulation on predator–prey relationships could be viewed as a computational model (vs. a diagrammatic model), a system model (vs. a mechanistic model), a scientific model (vs. a socio-scientific model), or an agent-based model (vs. a system dynamics model). Thus, it is crucial to explicitly define how we categorize models.

Aligned with our prior work, we categorize models into two broad categories: scientific models and socio-scientific models (Ke et al., 2021). This distinction is important because most models familiar to the science education and learning sciences community are scientific models. However, socio-scientific models, which consider social dimensions, are vital when reasoning about complex societal issues. We further categorize models based on their primary epistemic goals, for either scientific or socio-scientific models. For example, scientific models can be mechanistic models, system models, or data models, among others (Ke et al., 2021). In contrast, work on socio-scientific models is still emerging, and further categorization has not been attempted. The socio-scientific models used in our work have a primary epistemic goal of understanding complex issues from a systems perspective, making them system models within the broader socio-scientific model category.

Given the topic on systems thinking and modeling in this collected issue, we focus on system models in the scientific model category and system models in the socio-scientific model category in this paper. Hereafter, we use "system models" to refer to scientific system models and "socio-scientific model" to refer to socio-scientific system models, as the term "system model" in the literature typically refers to scientific system models.

In the following sections, we first briefly review relevant prior work in the areas of modeling, systems thinking, and SSI. We then highlight three major differences between socio-scientific models and system models. Next, we present an exploratory study of college students' engagement in socio-scientific modeling in the context of COVID-19. We conclude the paper by discussing implications of using socio-scientific models in classroom instruction.

Background

Scientific models and system thinking

In science, models play a crucial role in developing knowledge and theories that guide scientific inquiry and evidence-based reasoning (Nersessian, 2008). Models are simplified representations that visualize, describe, explain, and predict real-world phenomena or systems. Modeling is an epistemic practice that involves creating, revising, testing, and evaluating models. In K-12 science classroom, models and modeling are increasingly emphasized as effective pedagogical tools to help learners gain valuable insights into the practices and norms of scientists' work (Lehrer and Schauble, 2006; Windschitl et al., 2008; Schwarz et al., 2009; Manz, 2012; Krist et al., 2019; Ke and Schwarz, 2021). With appropriate instructional support, learners are able to develop and use models to make sense of underlying mechanisms and relationships within the natural world.

Models can take a variety of forms, including drawings, physical objects, computer simulations, mathematical equations, and more—each serving a unique purpose and providing insights into the underlying phenomena or systems (Schwarz et al., 2009). In our previous work, we argue that instead of focusing on their forms, it is useful to distinguish models based on their epistemic goals (Ke et al., 2021). This approach acknowledges the intrinsic link between the nature of model and its intended purpose in the process of scientific inquiry.

A common type of models in K-12 science education is system models that describe the constituent components and their interactions within a system (National Research Council, 2012). The primary epistemic goals of a system model are to understand the organization and predict the behaviors of the system (Assaraf and Orion, 2009; Bielik et al., 2022). Models can be particularly valuable in understanding and predicting behaviors of complex systems, such as ecosystems and cellular networks. A complex system comprises interacting components at multiple interacting levels (Wilensky and Resnick, 1999), and its aggregate nature cannot be easily predicted by merely examining the individual components in isolation. Prior research on science education has revealed that models are effective sensemaking tools for learners, helping them recognize two important features that characterize complex systems: causality and emergence (Yoon and Hmelo-Silver, 2017).

A complex system can have multiple causal factors that occur at different levels. Simple causal relationships often cannot account for the complex causality inherent in complex systems. Therefore, students often miss the connectedness and complex causal relationships within the system (Perkins and Grotzer, 2000). Hmelo-Silver and Pfeffer (2004) argued that a structure-behavior-function (SBF) model could help learners construct explanatory mechanisms about complex systems. They found that experts' behavioral and functional understanding served as a "deep principle" to organize their knowledge of complex systems. In contrast, novices like middle school students tended to focus only on the structure of a system. In a proof-of-concept study, Liu and Hmelo-Silver (2009) demonstrated that the SBF model could promote complex systems understanding, especially with respect to non-salient function and behaviors.

Emergence, another central concept of complex systems, is challenging for students to understand (Jacobson, 2001). This difficulty arises because emergent behaviors are often counterintuitive in nature and require thinking beyond the simple cause-and-effect relationships students are familiar with (e.g., feedback loops). Understanding emergence also calls for thinking at multiple levels, such as micro (individual), meso (clusters), and macro (the entire system). To address this challenge, Wilensky and his colleagues have extensively researched student learning about complex systems within computer-based multi-agent modeling environments such as NetLogo. NetLogo provides an interactive graphical environment that allows learners to visualize system components, explore their interactions, and observe emergent patterns in real-time. It supports the representation and analysis of multiple levels of a complex system, enabling students to explore connections between individual components and emergent system behaviors (Wilensky and Reisman, 2006).

Many complex systems can be viewed as causal, emergent, or both, depending on the levels of the systems being examined (Hmelo-Silver and Azevedo, 2006). This dual nature highlights the importance of understanding both the causal relationships and emergent properties inherent in complex systems. Regardless of the perspective, a modeling approach has been demonstrated to effectively support learners in developing system thinking skills that might otherwise be difficult to acquire.

Socio-scientific models and systems thinking about SSI

Socio-scientific issues, such as climate change, can be viewed as complex social systems, as they encompass multiple components that span both scientific and social dimensions (Ke et al., 2020). These components interact at different levels, ranging from individual (e.g., personal choices and behaviors) to community (e.g., community-shared values and practices) and societal scales (e.g., national policies and economic systems). The interconnectedness of these components across different levels creates a dynamic, complex system that demands a comprehensive understanding of the underlying causal relationships and emergent properties. By considering SSI as complex social systems, learners can better grasp the multifaceted nature of the issues and make informed decisions on the issues (Sadler et al., 2007).

Previous research on SSI has indicated that students often struggle to fully appreciate the complexity of the issues from a systems perspective (Hogan, 2002; Sadler et al., 2007). Instead of recognizing the multidimensional nature of SSI under study, students tend to pose relatively simple solution to SSI indicative of simple causal reasoning. They also find it challenging to take into account the social aspects of the issue. In fact, many teachers either feel uncomfortable about incorporating social dimensions into their teaching or are unsure of how to do so effectively (Tidemand and Nielsen, 2017; Hancock et al., 2019; Friedrichsen et al., 2021; Ke et al., 2023). Given the demonstrated success of modeling approaches to promote systems thinking across various scientific disciplines, it is worth exploring how the use of models could similarly enhance students' systems thinking about SSI.

A growing body of literature has begun to explore the integration of modeling and SSI (Evagorou and Puig-Mauriz, 2017; Zangori et al., 2017). For example, in our previous work, we found that high school students, with appropriate instructional and curriculum supports, developed robust scientific understanding about carbon cycling and climate change through modeling (Zangori et al., 2017). However, much of the research in the area, including our prior work, focuses on using scientific models to promote student understanding of scientific knowledge within the context of SSI, rather than using models to foster students' systems thinking about SSI.

In other words, most of the modeling-in-the-context-of-SSI work that has been conducted thus far does not directly support learners in connecting science to their everyday lives, much like traditional science teaching approaches. It falsely assumes that students, once equipped with relevant scientific knowledge, can readily apply it to real-world problems. As such, in our recent work, we proposed a new type of modeling, socio-scientific models, to leverage students' prior experience and knowledge about the social dimensions of underlying issue as students develop models in the context of SSI (Ke et al., 2021). The goal was to encourage students to construct new knowledge about how these issues connect to their own lives. Socio-scientific models are similar to system models in that they both involve systems thinking. However, there are subtle yet important epistemic differences between the two due to the introduction of social elements. It is crucial to be aware of how these epistemic differences might affect SSI teaching and learning.

Epistemic differences between socio-scientific models and system models

Investigating the epistemic dimensions of modeling practices is essential for fostering meaningful science teaching and learning (Pluta et al., 2011; Berland et al., 2016; Ke and Schwarz, 2021). It sheds light on how learners construct, evaluate, and validate scientific knowledge through modeling. Likewise, it is important to understand how students generate and justify their knowledge around SSI using socio-scientific models. Socio-scientific models incorporate social components, which calls for a different set of epistemic knowledge compared to system models or other models in the disciplines of science. In this section, we highlight three epistemic aspects where socio-scientific models differ from systems models, (1) knowledge representation, (2) knowledge justification, and (3) systems thinking.

Knowledge representation

A key epistemic consideration for any type of model is determining the relevant components or variables to represent the underlying phenomena or systems. With system models, learners must consider epistemic questions such as, what are the system's boundary? Which components or variables are important for representing and simplifying the system under study? These questions apply regardless of the type of systems being examined. For socio-scientific models, learners need to ask similar epistemic questions. What scientific and social components are relevant and important for the issue I am investigating?

Incorporating social dimensions in socio-scientific models is not trivial. It fundamentally changes how learners perceive the legitimacy of knowledge in science classrooms. Socio-scientific models encourage learners to integrate components from various disciplines such as policy, economics, or sociology, based on their relevancy to the issue. For example, when modeling climate change, learners might consider the impact of government policies on carbon emissions or the economic implications of transitioning to renewable energy sources.

Contrasting with system models that primarily value scientific ideas and principles, socio-scientific models rely on learners' understanding of various subject areas. This interdisciplinary modeling approach allows learners to explore the connections between science and other domains within complex societal issues. Consequently, scientific knowledge is not treated in isolation; instead, it is constructed and represented in relation to knowledge from other social disciplines, promoting a more integrated understanding of the issue being studied.

As such, when developing socio-scientific models as opposed to system models, learners must expand their knowledge representation beyond purely scientific dimensions. Not only do they need to ask themselves, "What scientific components do I need to include in my model?" but also delve into social aspects, asking, "What social components are relevant for the issue? How do the scientific components relate to the social components?"

Knowledge justification

Another important epistemic aspect of modeling is knowledge justification, which involves evaluating the validity of the knowledge being represented in a model. How can one determine if a model is correct? In system models, learners are expected to use scientific evidence and reasoning to justify their choices of components, relationships, and structure. In contrast, when developing socio-scientific models, learners must also consider social factors, ethical and moral implications, and multiple perspectives from different stakeholders. Therefore, socio-scientific modeling requires learners to provide justifications based on a broader range of evidence that may also include personal experiences, narratives, and values.

Moreover, knowledge justification in modeling not only concerns what constitutes evidence but also involves determining the robustness of that evidence. In system models, the evidential criteria are predominantly focused on how well the model is grounded within empirical data, how well it aligns with established scientific principles and theories, and how accurate it predicts system behaviors under various conditions. However, in socio-scientific models, the evidential criteria are more complex. In addition to evaluating empirical evidence based on different methodological traditions (e.g., qualitative, quantitative), learners also need to take into account factors such as how well the evidence represents diverse perspectives and marginalized communities, whether the evidence aligns with generally accepted ethical standards and moral principles, and how relevant or applicable the evidence is to the specific issues under study.

Take the issue of water scarcity for an example. When constructing socio-scientific models, learners may need to rely on various types of evidence to justify their models. This can include quantitative data such as precipitation and groundwater levels, as well as qualitative data gathered from interviews with local residents and experts. Furthermore, learners may also need to consider the ethical implications of different water management strategies, such as water privatization, and assess their impacts on marginalized populations. The justification process requires learners to apply different evidential criteria based on the type of evidence used. Due to the diverse evidential criteria involved in socio-scientific models, it can be challenging for learners to navigate them without adequate instructional support. Prior research in science education has highlighted the role of uncertainty as a productive pedagogical construct to promote students' disciplinary understandings (Manz and Suárez, 2018; Chen et al., 2019). We argue that making explicit the uncertainty inherent in social sciences due to various evidential criteria used in socio-scientific models could likewise enhance learner's appreciation of the complexity of societal issues.

Systems thinking

One epistemic aspect specific to socio-scientific models is systems thinking from a broader social science perspective. The goal of this form of thinking is to understand complex societal issues by examining interrelationships, feedback loops, and emergent properties within social, economic, and political systems, where human behavior, values, and decision-making are crucial factors. Systems thinking in socio-scientific models differs from systems thinking in scientific disciplines due to the contrasting epistemic foundations. While scientific disciplines primarily emphasize objectivity, quantifiability, and replicability, social sciences prioritize diverse perspectives, qualitative data, and the complexities of human interactions within systems. So how might systems thinking look different in socio-scientific models?

The levels in a socio-scientific model are often different from those in a system model due to the inclusion of social components and human involvement. Socio-scientific models often feature a multi-level structure, with personal, community, and societal levels. Different relationships can exist at each level, making it challenging to predict behaviors across them. The multi-level nature of systems in socio-scientific models is closely tied to values and priorities, which are essential factors in decision-making for SSI. For instance, when addressing air pollution, an individual may choose biking based on their personal values and priorities. However, this choice does not guarantee a community investment in bike lanes, as it also depends on community values and local resources. At the society level, governments might implement loose emission standards for vehicles to stimulate the economy, which prioritizes short-term economic gains over long term environmental and public health concerns.

Another area where socio-scientific models differ from systems models in terms of systems thinking is causality. While complex causality can be involved in system models, as noted above, causal relationships in socio-scientific models are often more nuanced. This is due to potential biases and assumptions held by researchers when interpreting causal relationships in social sciences, even when established through rigorous methods like experimental designs or advanced statistical techniques. Furthermore, causal relationships in social sciences can be highly context-dependent, varying across different populations, cultures, and time periods. Thus, it is essential to consider the specific context in which causal relationships are established.

In many instances, establishing causality is challenging, leading to a focus on correlation rather than causation. While correlations do not necessarily imply causation, they can still provide insights into how variables are connected and interact within the system. For instance, in the context of public health, there is often a correlation between socioeconomic status and overall health outcomes. Although it may not be possible to establish a causal relationship between these factors, understanding the correlation can help identify patterns and inform policy decisions. Additionally, recognizing correlation necessitates an understanding of uncertainty. Uncertainty refers to the degree of doubt in the relationships between the variables. By quantifying uncertainty, we can better understand the limitations of the correlation and make more informed decisions based on the available data.

An exploratory investigation

In the previous section, we examined three epistemic differences between socio-scientific models and system models from a conceptual standpoint. We argue that these differences can have important implications for SSI teaching and learning. To further this work, we conducted an exploratory study to investigate how learners respond to these three epistemic differences. We aimed to gain insights into the challenges and opportunities learners encounter while engaging in socio-scientific modeling activities. Specifically, we ask the research question: *How do learners develop a socio-scientific model on COVID-19 with respect to knowledge representation, knowledge justification, and systems thinking?*

The findings from this exploratory study will contribute to our understanding of how learners make sense of and coordinate both scientific and social components of the underlying issue within the context of socio-scientific models. Additionally, the findings will inform our design of socio-scientific modeling activities, making them more meaningful and accessible for learners. This study is exploratory because little research has been conducted on socio-scientific models and we focus specifically on learners' use of epistemic ideas represented in in socio-scientific models. Although the sample size is small, the goal is not to make generalized claims; instead, we aim to provide empirical evidence that illustrates what these epistemic ideas might look like in the context of socio-scientific models.

Research context and participants

This study investigated collaborative construction of socio-scientific models among six female college-age students at a large public research university in the southeastern United States. Participants were recruited through convenience sampling and consisted of three pairs: one consisting of an African American female (Tia, a psychology major) and a Latina (Clara, an English major), and two pairs of white high school graduates (Sally & Stephanie, Aria & Chloe). All pairs know each other well. The study took place on the university campus spring 2022 and it was not associated with any science-related coursework. The study design involved an initial 30-min session where the first author guided each pair in constructing a socio-scientific model on local river water quality, familiarizing them with the processes and norms (e.g., adding arrows to indicate the direction of causal relationships) involved. The participants were then asked to collaboratively develop a COVID-19 socio-scientific model on a whiteboard in approximately 20 min. During the process, the participants were encouraged to think aloud and to discuss with each other what to and not to include in their models. Upon completion, each student participated in a semi-structured interview, reflecting on their experiences in constructing the socio-scientific models.

Socio-scientific models

We selected COVID-19 as the focal issue for the socio-scientific models, assuming that participants would be familiar with both scientific and social dimensions of the issue. This choice was appropriate, as no instructional intervention about the focal issue was involved, and participants had no prior experience with socio-scientific models. As a result, we designed the initial session to familiarize participants with this type of model.

During the initial session, we provided scaffolds to support learners in the following aspects. We divided the process of creating socio-scientific models into two steps, (1) identifying key factors relevant to the system and (2) establishing relationships between these factors. When identifying key factors, we prompted learners to consider both scientific and social components. We illustrated that pesticides washing into a river, a scientific component, could be one factor affecting water quality. In turn, the water quality would influence the money spent cleaning the river, an economic component relevant to the issue. Figure 1 was one of the slides used during the initial session.

We then demonstrated that arrows could be used to represent causal relationships. We also informed learners that not all factors had obvious causal relationships; some factors might be closely correlated. To encourage learners to consider the system dynamics of the underlying issue, we introduced conventions of "+" and "-" signs to represent positive and negative causal/correlation relationships. For instance, a negative sign between pesticides washing into a river and water quality indicates that an increase in pesticide use will result in decreased water quality. This approach prompted learners to think about causal or correlational relationships in a semi-quantitative manner. After familiarizing the participants with the process and conventions, we asked them to identify factors and relationships they deemed significant for the issue of water quality on their own.

For the COVID-19 socio-scientific model, we gave participants the driving question, "how has COVID-19 impacted your life?" We encouraged participants to consider relevant factors that encompassed both scientific and social components. Additionally,

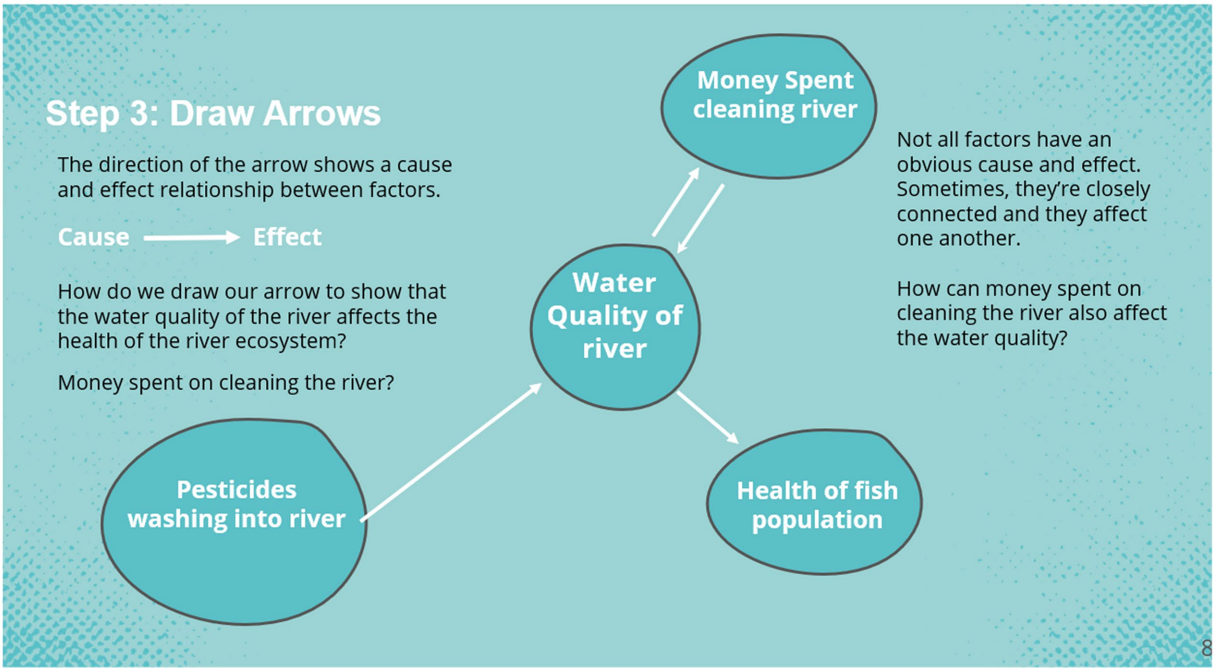

FIGURE 1
The slide used in the initial session to introduce socio-scientific models.

we provided participants with the component, COVID-19 infection rates, at the center of the whiteboard, allowing them to start creating the model with factors affected or were affected by COVID-19 infection rates.

Data sources and analysis

The primary data sources for this study were video recordings of participants working on their COVID-19 socio-scientific models and individual interviews. The video recordings captured the detailed process of creating socio-scientific models and the negotiation between pairs. The interviews focused on participants' reflections concerning the epistemic dimensions of the modeling process, as well as the perceived affordances and challenges of socio-scientific models. We selected these sources as they provided evidence of participants' epistemic ideas used during the socio-scientific modeling process. The video recordings offered in-the-moment data as participants were encouraged to think aloud. The interviews provided reflective data on students' epistemic ideas, allowing us to inquire about ideas not explicitly mentioned during the session. Both sources were transcribed for data analysis. We also used the socio-scientific models participants developed as supplementary evidence to inform and triangulate our analysis.

To address the research question, we compared and contrasted data among the three pairs concerning knowledge representation, knowledge justification, and systems thinking in the socio-scientific modeling activities. We used the constant comparative approach (Glaser and Strauss, 1967) to develop codes that were subsequently modified and aggregated into emergent themes. Given the small sample size and the exploratory nature of the study, we do not present the frequency of the emerging themes. Instead, in the following findings section, we highlight the patterns observed across the three pairs and trends that were unique to specific pairs.

Findings

Knowledge representation

Regarding knowledge representation, all three pairs incorporated various social factors into their COVID-19 models, including economic, educational, public health, and policy elements. For example, Tia and Clara from Pair 1 incorporated employment, mental health, international travel policies, and remote teaching into their model (see Figure 2).

Additionally, the interview data revealed that participants chose these social components because they were personal and relevant to them. For instance, Sally and Stephanie from Pair 2 incorporated virtual schooling into their model because they lived in the same area and had similar experiences with online learning. Likewise, Chloe from Pair 3 included lockdown, quarantine, and labor shortage in their model because she had recently contracted COVID-19 and her family's small business was significantly affected by labor shortages.

One interesting pattern we observed was that most factors identified by the participants were social components. Only Pair 3 included a few scientific components, such as vaccines and testing, and their potential impact on reducing COVID-19 infection rates. While it was possible that participants were more familiar with the social dimensions of COVID-19 (compared to other issues such as climate change), based on the data, we hypothesized that this pattern might be attributed to the

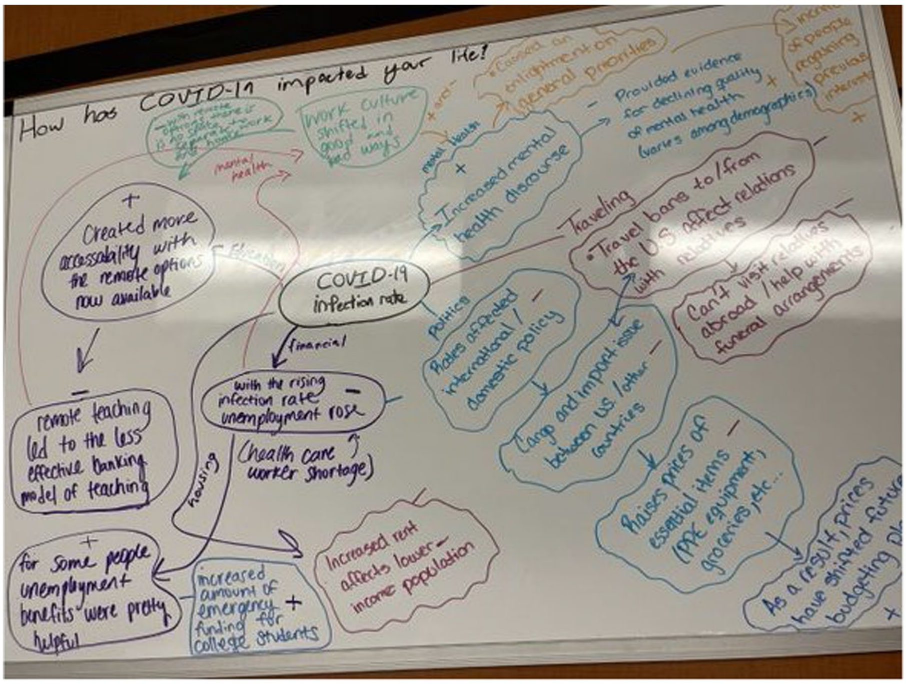

FIGURE 2
Tia and Clara's COVID-19 socio-scientific model.

participants' backgrounds. The excerpt below, from Clara's interview, reveals that they did not include scientific components mainly due to their humanities backgrounds. Instead, they chose to include social components that were relevant to them.

> I think if you would have asked two different people, maybe someone who was like in a science field, they would go into how the infection rate affects your health wise. But because Tia and I are kind of both into like humanities, we did focus. And we're both people of color. So, we both like wrote down ways that affected us and that's why, and our things are kind of unique to our experiences. (Clara, Pair 1)

Knowledge justification

Regarding knowledge justification, participants leveraged various sources of evidence to establish relationships within their models. Personal narratives emerged as the primary source upon which participants relied. As these narratives were based on their own experiences, participants felt it was legitimate to include them in the model. For instance, in Pair 1, Clara drew from her experience of losing a family member to justify a relationship between mortality rates and travel ban, and how these travel bans impacted people's lives and cultures.

> Clara: families had lost people, family members. I know that like particularly for –.
> Tia: So you want another one to be like mortality rates?
> Clara: Yeah, could you write that?
> Tia: Yeah, mortality, okay, what do you want to say about that?
> Clara: I know that I did have family members who passed away in other countries because, um - and you just - you are not able to - you are not able to, I do not know, travel.
> Tia: Oh, that could be another one, the traveling. There were like a lot of travel bans.
> Clara: When my uncle died, we were not able to go to Mexico, even his family were not even able to be with him.
> …
> (Towards the end of the session, when asked to explain the model)
> Clara: We tried to incorporate mortality rates into that because that is an immediate effect of the infection rates, sadly. Some of the biggest issues with not being able to travel is that you cannot directly help with funeral arrangements. And we know in certain cultures that's a really big deal, especially doing it properly.

Our findings revealed that, across all three pairs, participants were often uncertain about many of the relationships they identified in their models if they were not related to their personal experiences. Uncertainty was a common theme among the participants. As one participant reflected, "a challenge (of creating a socio-scientific model) would be the lack of credibility." Participants expressed a lack of confidence in the relationships, mainly because they had not conducted extensive research on the topic and might have only encountered the information through news sources or social media platforms like TikTok.

Furthermore, some of the uncertainty expressed by participants originated from the complex nature of epistemic knowledge in social sciences. For example, Chloe from Pair 3 described her struggle with establishing relationships in their model during her interview:

Like with lockdowns, we could not quite place like do we put it as a cause or an effect. I guess there's room for, subjectivity or opinions, kind of, just in like where everything is. And also, I do not know, I think you could argue some of these things are like they could be positive or negative, instead of just one or the other. (Chloe, Pair 3)

In the excerpt, Chloe mentioned the "subjectivity" involved in determining relationships among social components, stating, "just like where everything is." To her, the causal relationships were not apparent among some the components they had selected.

For the relationships in which participants felt confident, the primary epistemic criterion used by all participants was whether it made sense to them. For example, Stephanie from Pair 2 remarked, "We just kind of knew that, okay, these things are related. Like it makes sense. We only stuck with what made sense to us. So in our minds, it was right." Likewise, Aria from Pair 3 stated, "I just pictured in my brain, making sure it makes sense. And if it does not, then I try and find something different."

Systems thinking

Regarding system thinking, most participants noted that one of the affordances of socio-scientific models was their ability to help them see the connections among relevant components that they might otherwise not consider. The following quote from Tia's interview is representative of how participants perceived the advantage of socio-scientific models:

> If I hadn't seen it all put together like this, I wouldn't have been able to make the connections where these two things (work culture and public discourse) are connected to mental health, and now it's visually here so I can see that. (Tia, Pair 1)

Furthermore, with the scaffolds of positive and negative signs, all participants were able to reason, to varying degrees, about the systems dynamics of the underlying issue. For instance, Stephanie from Pair 2 explained their model (see Figure 3) during the session:

> Infection rates, we start with the basics, you know, social distancing, mask mandates, businesses closing down, and quarantine. And those led into bigger issues. So, quarantine led to mental illness because you're away from people, your mental health deteriorates. And then social distancing led to relationship impact, which was also connected to mental illness.

As evident in the excerpt, Stephanie was able to use a chain of reasoning to explain how an increase in infection rates could result in mental illness through intermediate factors such as quarantine and social distancing policies.

Another common pattern we observed was how participants considered factors and relationships at different levels: personal and family, community and specific groups of people, and national or international societal level. Interestingly, each pair seemed to have unique approaches. For pair 1, Tia and Clara, they started with the most personal and relevant factors, themselves and their family members, and they moved on to groups of people with whom they could resonate. Below is the excerpt from Tia's interview when asked about her strategy to create the model:

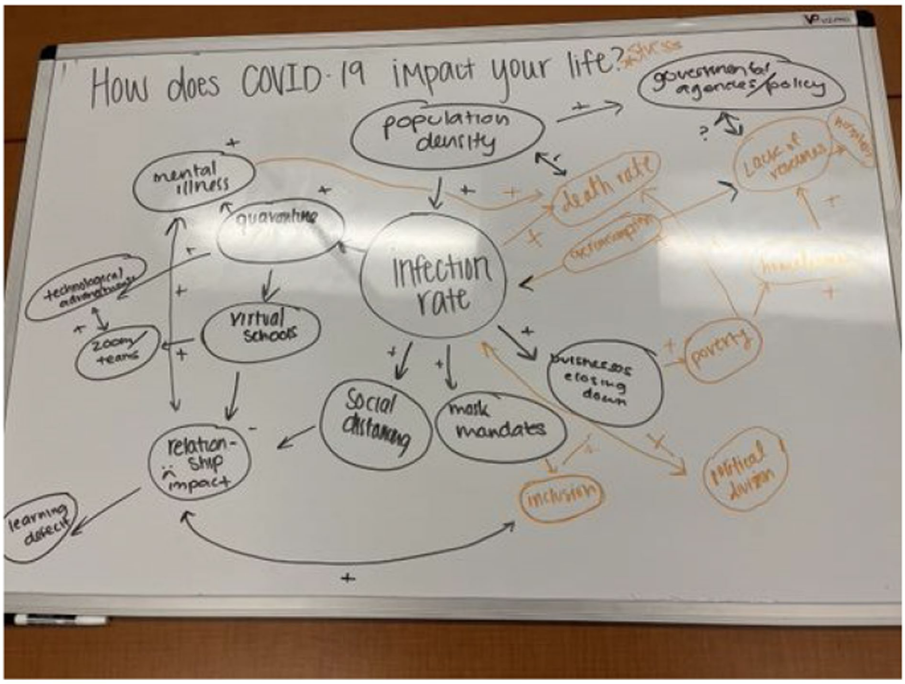

FIGURE 3
Sally and Stephanie's COVID-19 socio-scientific model.

> I went with the most important ways like the biggest impacts that it had. I started with myself and education, because that's just the biggest thing I have going on right now. And then, I went from like family members which is financial, which is the most important thing that my mom has going on. And then I went from there.
>
> I felt that we got really personal. We did reflect a lot on what affected us more. So, what affected other populations that we weren't familiar with? We had a lot to say about the housing and mental health, especially as college students who aren't from affluent neighborhoods or anything. So, we definitely had a lot to say about that, because it was more personal. (Tia, Pair 1)

In contrast, Aria and Chloe from Pair 3 took an opposite approach. While still drawing from their personal experiences, they were hesitant to include too many personal level components in the model. The excerpt below explains their rationale for emphasizing more on the societal level:

> I think, overall, we were listing like scientific explanations, and not as much personal. I guess I was able to think back to my time. But also, at the same time, we didn't list that many personal things, so I didn't see my experiences in it as much. I think we were listing more general, like the world, the impacts on society actually. (Aria, Pair 3)

It appeared that Aria and Chloe's focus on the societal level was because they believed it might be more "scientific." This also reflects that they might prefer a large sample size over personal experiences based on their evidential criteria.

Indeed, there seemed to be a tension between whether to focus more on the personal level or the larger societal level. What makes this complex is that different levels also involve different values and perspectives. For instance, Clara from Pair 1 made the following comment, highlighting the tension she felt when trying to make the model personal, while also wanting to account for various perspectives and experiences:

> It was difficult to decide whether it was a positive or a negative relationship. We can't really see it just from our perspective, as we mentioned earlier. It was kind of thinking outside of yourself, like, the unemployment that we mentioned, and the funding received for that. Well, for some families who are already making like maybe underneath what is deemed as the poverty line, that would have been a humongous help, because that's a grant that's more than what you've actually been working towards. But for other families, that probably just wasn't enough. So, it really depends on the situation. And we tried to not be biased, because we tried to make it personal. But at the same time, there are so many people in this world affected by the pandemic, and we really can't account for all of their perspectives and experiences just from our generalizations. (Clara, Pair 1)

For Clara, her struggle with the contextual nature of some of her claims highlights the epistemic difference between science and social sciences. It is likely that she was not very familiar with the context-based aspect of social sciences. Sally from Pair 2 shared the same sentiment, expressing that she could not speak for something that she had not personally experienced. She noted, "The things that were not as directly affecting me like poverty, I wasn't affected by poverty. My parents did not lose their jobs. I do not know. It felt like, I cannot really speak for this. But this is just like from outward looking in."

Discussion and implication

The findings of this study demonstrated that, due to the epistemic difference from traditional scientific modeling approach, engaging learners in developing socio-scientific models presents unique opportunities and challenges for learners for SSI teaching and learning. The inclusion of social elements enabled learners to leverage their personal experiences, values, and perspectives into the modeling process. At the same time, socio-scientific models can be challenging for learners. Being unfamiliar with certain epistemic traditions in social sciences hindered learners from fully realizing the potential of socio-scientific models and using them to make informed decisions on issues that mattered to them. In the following section, we discuss how socio-scientific modeling can promote diversity, equity, and inclusion in science classrooms and what additional supports are needed for socio-scientific modeling to be meaningful for learners. We conclude the section with suggestions for future research.

Socio-scientific models to promote diversity, equity, and inclusion

An important finding of the study was the critical role personal experiences or narratives play in the development of socio-scientific models. This was evident in all three epistemic aspects of the model-building process. During knowledge representation, most learners selected social components based on their personal experiences. In knowledge justification, the majority of learners used personal experiences as evidence to justify their model components. Regarding systems thinking, some learners preferred to start with components and relationships at the personal level and then progressed towards community and societal levels.

This emphasis on learners' personal experiences makes socio-scientific models a productive approach for promoting diversity, equity, and inclusion (Schwarz et al., 2022). Fundamentally, socio-scientific models disrupt the traditional notion of legitimate knowledge and embrace diverse voices and perspectives in science classrooms. By highlighting personal experiences, socio-scientific models empower learners from marginalized communities to contribute their unique perspectives and knowledge to classroom discourse, as exemplified in Tia and Clara's case. This approach can also enrich the learning experience for all learners by exposing them to a broader array of viewpoints and experiences.

From a systems thinking perspective, socio-scientific models can also promote science learning for social-justice. By exploring complex societal issues at the community level, students can gain a better understanding of the systemic factors contributing to structural inequalities affecting marginalized communities and work towards developing potential solutions. For instance, in their socio-scientific models, our participants identified historically marginalized individuals such as people living in poverty, immigrants with distant families, and those who lost their jobs. and how the pandemic disproportionally affected these groups. Focusing on social justice issues within the context of SSI can foster a more inclusive and equitable learning environment while also promoting empathy and civic engagement among students (Calabrese Barton et al., 2021; Rawson Lesnefsky et al., 2023).

Additional supports for socio-scientific modeling

The present study showed various challenges learners face as they engage in socio-scientific modeling. Additional supports are needed to further scaffold the modeling process and make it meaningful for all learners. One major challenge learners encountered was related to the epistemic traditions in social sciences. Participants from all three pairs were unfamiliar with, and therefore uncomfortable with the uncertainty involved in determining the relationships among social components and the tensions in balancing multiple perspectives at different systematic levels.

As such, learners need supports in navigating these epistemic ideas that may differ significantly from those they are accustomed to in science. For example, providing explicit instruction on how personal narratives, qualitative data, and different perspectives are valued in social sciences could be potentially helpful. In addition, learners would benefit from understanding how uncertainty or probability plays a role in our comprehension of correlational relationships, and how these relationships can be highly context specific.

Another significant challenge learners faced was a lack of sufficient evidence to justify their models. This, in part, contributed to the uncertainty learners experienced as they determined the relationships among components. Participants in this study had to primarily rely on their personal judgments to determine the validity of the relationships, considering whether they made sense to them or not. This justification process could lead learners to a false sense that everything was connected. Therefore, to help learners systematically understand the complexity of the underlying issue, more evidence is needed, either by encouraging learners to seek evidence on their own or providing them with a variety of evidence sources. By doing so, learners can have the opportunity to learn how to use and evaluate different types of evidence for knowledge justification in the context of socio-scientific models.

One limitation of the socio-scientific model described in this study is its paper-pencil format. Due to technological constraints, it primarily emphasizes the causality aspect of systems thinking, and limits attention to emergence as a feature of systems. To further support learners in understanding emergent outcomes, computational technologies, such as NetLogo, may be helpful. For example, in its current form, learners can reason about system dynamics in a semi-quantitative way as evident in our data, but it was challenging, if not impossible for them to predict system outcomes with high quantitative accuracy. However, with the support of computational tools, achieving more accurate predictions might be possible.

Direction for future research

Given initial results of this study, we suggest further exploration in the following three areas. First, additional empirical evidence should be gathered to demonstrate how using socio-scientific models can facilitate equitable learning opportunities for students, especially those from underrepresented populations, across a range of SSI topics. This is important as students may have diverse reactions to different SSI topics, and we need to figure out how to best leverage students' prior knowledge and experiences. Second, further research is needed to investigate how learners use different epistemic understandings and evidential criteria to develop socio-scientific models. This link between students' epistemic ideas and modeling practice is crucial for making instruction meaningful for all learners. Third, we need to learn more about how to adequately evaluate socio-scientific models. Given the distinct epistemic understandings and criteria used in socio-scientific models, a new framework needs to be developed to assess how well the socio-scientific models capture the system dynamics of the target complex issue, including both science and social dimensions.

Conclusion

As the world faces complex societal challenges, including the global pandemic, it is more critical than ever to prepare our future generations to be scientifically literate and responsible citizens. SSI teaching and learning have the potential to achieve this goal, yet many teachers find it challenging to address the social aspects of complex societal issues. This paper provides evidence that, socio-scientific models can serve as not only an effective but also an equitable tool for addressing this issue. The three epistemic features highlighted in this paper contributed new knowledge for fostering meaningful SSI-based instruction. By focusing on these features, science educators can better support learners in understanding the complexity of the underlying issues while empowering them to become informed citizens capable of tackling pressing societal issues.

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 humans were approved by University of North Carolina at Chapel Hill. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

LK, EK, TS, and RL contributed to the conceptualization and design of the study. LK, EK, and RL collected, organized, and analyzed the data. LK wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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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.

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EDITED BY
Laura Zangori,
University of Missouri, United States

REVIEWED BY
Agustín Adúriz-Bravo,
University of Buenos Aires, Argentina
Emil Eidin,
University of Wyoming, United States
Jaime Sabel,
University of Memphis, United States

*CORRESPONDENCE
Paul Engelschalt
paul.engelschalt@hu-berlin.de

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Abductive reasoning in modeling biological phenomena as complex systems

Paul Engelschalt[1]*, Maxime Röske[1], Johanna Penzlin[1], Dirk Krüger[2] and Annette Upmeier zu Belzen[1]

[1]Biology Education, Institute of Biology, Humboldt-Universität zu Berlin, Berlin, Germany, [2]Biology Education, Institute of Biology, Freie Universität Berlin, Berlin, Germany

Introduction: Abductive reasoning is a type of reasoning that is applied to generate causal explanations. Modeling for inquiry is an important practice in science and science education that involves constructing models as causal explanations for scientific phenomena. Thus, abductive reasoning is applied in modeling for inquiry. Biological phenomena are often best explained as complex systems, which means that their explanations ideally include causes and mechanisms on different organizational levels. In this study, we investigate the role of abductive reasoning in modeling for inquiry and its potential for explaining biological phenomena as complex systems.

Methods: Eighteen pre-service science teachers were randomly assigned to model one of two biological phenomena: either a person's reddened face, for which participants knew of explanations from their everyday lives, or a clownfish changing its sex, for which participants did not know about explanations. Using the think-aloud method, we examined the presence of abductive reasoning in participants' modeling processes. We also analyzed modeling processes in terms of participants' ability to model the phenomena as complex systems.

Results: All participants reasoned abductively when solving the modeling task. However, modeling processes differed depending on the phenomenon. For the reddened face, participants generated simple models that they were confident with. In contrast, for the clownfish, participants generated more complex models that they were insecure about. Extensive engagement in abductive reasoning alone did not lead to the generation of models that explained the phenomena as complex systems.

Discussion: Based on the findings, we conclude that engagement in abductive reasoning will not suffice to explain phenomena as complex systems. We suggest examining in future studies how abductive reasoning is combined with systems thinking skills to explain phenomena as complex systems in biological model construction.

KEYWORDS

reasoning, modeling, abduction, explanation, inquiry, complexity, systems thinking (ST), mechanism

1. Introduction

Modeling is a key practice in science (Koponen, 2007; Lehrer and Schauble, 2015; Frigg and Hartmann, 2020) and, thus, a central practice in standards for science education (OECD, 2008; NGSS Lead States, 2013; KMK, 2020). In science and science education, modeling has two functions. One is *representational modeling*, where a model is constructed as a focused representation of the phenomenon and is applied as a medium for communicating about the phenomenon (Oh and Oh, 2011; Gouvea and Passmore, 2017; Upmeier zu Belzen et al., 2021). The other function is *modeling for inquiry*, where a model is constructed as a possible explanation for the phenomenon, and it is applied as a research tool for deriving hypotheses and conducting investigations to test them (Oh and Oh, 2011; Gouvea and Passmore, 2017; Upmeier zu Belzen et al., 2021). Both functions of modeling deal with the explanation of phenomena, but they refer to different meanings of explaining (Rocksén, 2016; Ke and Schwarz, 2019; Upmeier zu Belzen et al., 2021): while representational modeling is about explaining to *make something clear* about a well-studied phenomenon, modeling for inquiry is about explaining *to justify something* about a so-far-explained phenomenon. In both explanatory senses, and thus in both functions of modeling, biological phenomena are often best explained as complex systems (Hmelo-Silver et al., 2017; Snapir et al., 2017). A phenomenon is explained as a complex system if its explanation includes causes and mechanisms on different organizational levels (Schneeweiß and Gropengießer, 2019, 2022; Ben Zvi Assaraf and Knippels, 2022; Penzlin et al., 2022).

Systems thinking is conceptualized as higher-order thinking skills that help learners to "make sense of complexity" (Ben Zvi Assaraf and Knippels, 2022, p. 250). Thus, systems thinking skills are needed to explain biological phenomena as complex systems. Scholars have argued that modeling scaffolds learners in applying systems thinking skills by providing a focused representation of complex phenomena (Ben Zvi Assaraf and Knippels, 2022; Dauer et al., 2022; Tamir et al., 2023). This bridges representational modeling and systems thinking skills.

Although representational modeling is highly important to teach content knowledge about concrete phenomena (Stieff et al., 2016; Upmeier zu Belzen et al., 2019) in science and biology education, it is "insufficient to capture the full scope of the function of models" (Cheng et al., 2021, p. 308). Therefore, it is also important to consider the function of modeling for inquiry and its relation to systems thinking in science and biology education (Passmore et al., 2014; Gouvea and Passmore, 2017). Adding to the bridge between representational modeling and systems thinking skills, we propose to link systems thinking skills and modeling for inquiry: modeling for inquiry involves generating explanations for so-far-unexplained phenomena (e.g., Gouvea and Passmore, 2017; Upmeier zu Belzen et al., 2021). Thus, systems thinking skills are needed in modeling for inquiry to explain so-far-unexplained phenomena as complex systems.

Abductive reasoning is defined as the type of reasoning that generates causal explanations (e.g., Peirce, 1978; Magnani, 2004). It has been stated that abductive reasoning is the primary mode in model construction for inquiry (e.g., Svoboda and Passmore, 2013; Oh, 2019). Modelers apply abductive reasoning in model construction when they generate novel explanations using creative analogies or when they select between concurring explanations (Clement, 2008; Schurz, 2008). This important role of abductive reasoning in modeling for inquiry in biology has been justified by historical analysis of modeling processes leading to important ideas in biology (Adúriz-Bravo and González Galli, 2022), theoretical argumentations (Upmeier zu Belzen et al., 2021), and case studies (Clement, 2008; Svoboda and Passmore, 2013). In this study, we aim to add to these findings by examining the role of abductive reasoning in modeling for inquiry and the relationships between abductive reasoning and the ability to explain biological phenomena as complex systems. Generated inferences will contribute to research by providing further empirical arguments discussing the role of abductive reasoning in modeling of complex biological phenomena. In addition, the findings of this study should help to develop instructional strategies for modeling of phenomena as complex systems in biology education.

2. Theoretical background

2.1. Modeling for inquiry in biology education

We conceptualize modeling for inquiry as the iteration between model construction and model application (Krell et al., 2019; Upmeier zu Belzen et al., 2021). This concept of modeling is supported by empirical evidence from studies that have examined the modeling processes of middle-school students (Meister and Upmeier zu Belzen, 2020) as well as pre-service biology teachers (Göhner and Krell, 2020; Meister et al., 2021; Göhner et al., 2022) and matches concepts of modeling among other researchers who use similar terminology (*constructing and evaluating models*, see Cheng et al., 2021; *construct and improve models*, see Nicolaou and Constantinou, 2014, p. 53; *creating and using models*, see Oh, 2019).

In modeling for inquiry, model construction is about generating a plausible explanation for a so-far-unexplained phenomenon (Gouvea and Passmore, 2017; Upmeier zu Belzen et al., 2021). Based on this perspective, a generated explanation for a phenomenon is the product of model construction and conceptualized as *the model* (Rohwer and Rice, 2016; Rice et al., 2019). Scientific inquiry aims to find causal explanations, i.e., to explain why and how phenomena emerge (Perkins and Grotzer, 2005; Haskel-Ittah, 2022). Causal explanations should at least provide a cause for *why* phenomena occur. Ideally, causal explanations in science combine a cause with a concrete mechanism that explains not only *why* but also *how* phenomena have emerged (Salmon, 1990; Alameh et al., 2022; Penzlin et al., 2022). Different modelers have different views of what counts as a satisfying explanation (Cheng et al., 2021). However, if a modeler has generated a plausible explanation for themselves, then "model construction temporarily ends" (Upmeier zu Belzen et al., 2021, p. 4). In the following stage of model application, the generated explanatory model is used to derive predictions and strategies to test them with inquiry methods, such as experiments or observations (Giere, 2009; Gouvea and Passmore, 2017; Upmeier zu Belzen et al., 2021).

2.2. Abductive reasoning in modeling for inquiry

Different stages of scientific inquiry are connected to different types of reasoning (Lawson, 2003, 2010; Adúriz-Bravo and Sans Pinillos, 2019). The relationships between and definitions of reasoning types in inquiry are discussed in the philosophy of science literature (e.g., Kuipers, 2004; Adúriz-Bravo and González Galli, 2022). According to Peirce (1978), induction, deduction, and abduction are the types of reasoning that are involved in scientific inquiry. Within the Peircean framework, inductive reasoning is defined as generalizing from observations, deductive reasoning as predicting based on existing theories or rules, and abduction as generating and selecting causal explanations. The example of observing a wet sidewalk has previously been used to illustrate these reasoning processes (e.g., Adúriz-Bravo and González Galli, 2022). Using inductive reasoning, one would generalize that all sidewalks are wet. Using deductive reasoning, one would predict that the next sidewalk one walks on will also be wet. Using abductive reasoning, one could generate the explanation that the wet sidewalk is caused by cleaning activity in the city, but upon considering that people are walking with raincoats and seeing gray clouds in the sky, one would decide that the wet sidewalk having been caused by rain is a more plausible explanation.

The three reasoning types are involved in modeling for inquiry (Upmeier zu Belzen et al., 2021). Induction is involved if models are constructed based on the generalization of observations. Induction leads to testable models but does not bring new ideas into modeling for inquiry (Wirth, 2003; Magnani, 2004; Upmeier zu Belzen et al., 2021). New ideas in model construction are generated by abductive reasoning (Wirth, 2003; Magnani, 2004; Upmeier zu Belzen et al., 2021), since abduction is about generating causal explanations for a phenomenon and selecting between them. Deductive reasoning is involved in model application when using models to derive predictions that act as hypotheses for planning and conducting further inquiry into the phenomenon (Dunbar, 2000; Giere et al., 2006; Halloun, 2007). In this study, we focus on abductive reasoning. We operationalize this by applying the theoretical concepts of the *steps of abduction* that have been proposed in a cognitive psychological framework of abductive reasoning (Johnson and Krems, 2001; Baumann et al., 2007) and the *patterns of abduction* that are described in the philosophy of science literature (Habermas, 1968; Wirth, 2003; Schurz, 2008).

2.2.1. Steps of abduction

In their framework, Johnson and Krems (2001) proposed seven *steps of abduction*, which are not taken in a fixed sequence; hence, they interact with each other and depend on situational preconditions. In our study, we use six of the steps to operationalize abductive reasoning in model construction (Table 1).

TABLE 1 Steps of abduction, adapted from Johnson and Krems (2001).

Step	Description
Collect data	Modelers observe a phenomenon and gather information.
Comprehend	Modelers integrate collected data into their prior knowledge to generate a primary explanation for the phenomenon.
Refine	Modelers specify on explanations, for instance by combining multiple explanations or by generating a mechanism.
Discriminate	Modelers select between explanations and decide which explanation is worth further investigation.
Check	Modelers evaluate the logical consistency of explanations.
Resolve anomaly	Modelers eliminate logical inconsistencies from an explanation.

Test is another step proposed in Johnson and Krems's (2001) framework of abductive reasoning. The *test* step is about developing strategies (e.g., experiments) to further investigate the generated model. Those testing strategies are ideally based on model-derived predictive hypotheses (Giere et al., 2006; Godfrey-Smith, 2006). Deductive reasoning is considered to be the type of logical reasoning that leads to predictive hypotheses about a phenomenon. Thus, we do not refer to the *test* step as a step in abductive reasoning in model construction, but rather as the step that indicates the transition from abductive reasoning in model construction to deductive reasoning in model application (Upmeier zu Belzen et al., 2019, 2021).

2.2.2. Patterns of abduction

The pattern of abduction that is applied in modeling for inquiry depends on how much modelers already know about possible explanations for a phenomenon (Habermas, 1968; Wirth, 2003; Schurz, 2008). The pattern of *creative abduction* is applied if modelers do not know possible explanations for the phenomenon (Schurz, 2008). Thus, they need to create a novel one, e.g., by creating analogies, which means transferring knowledge from other contexts (Clement, 2008). When Darwin observed the diversity of finches with different beak shapes and diets, he explained it through the concept of a common ancestor and evolution by natural selection over time. This was a novel explanation that he generated creatively based on the analogy of change in domesticated animals under human selection (Adúriz-Bravo and González Galli, 2022). The pattern of *selective abduction* is applied if modelers know about explanations (or at least about concrete causes) for the phenomenon and need to apply their knowledge to select plausible ones (Schurz, 2008). For example, if a patient presents with a common symptom such as high blood pressure, a doctor needs to apply knowledge of the patient's medical history to select one among many possible explanations for the symptom.

2.3. Complexity and systems thinking skills in biology education

Biology is the science of life (Hillis et al., 2020). Biological phenomena are observable processes or events that occur within or involving living organisms at various levels of organization, from molecular to populational or biosphere levels. Since interactions among these levels result in emergent properties (Schneeweiß and Gropengießer, 2019, 2022), biological phenomena are inherently complex (e.g., Ben Zvi Assaraf and Knippels, 2022; Haskel-Ittah, 2022) and best explained as complex systems (Duncan, 2007; Hmelo-Silver et al., 2017; Snapir et al., 2017). A biological phenomenon is explained as a complex system if its explanation involves causes and mechanisms at different levels of organization (Schneeweiß and Gropengießer, 2019, 2022; Penzlin et al., 2022). As systems thinking skills help learners to understand and interpret complex systems (Dor-Haim and Ben Zvi Assaraf, 2022), they are needed to explain biological phenomena (Verhoeff et al., 2018). Among others, cross-level reasoning and identification of system components and relationships are important systems thinking skills

(Tamir et al., 2023). These skills are addressed in the **c**omponent **m**echanism **p**henomena (CMP) approach by Hmelo-Silver et al. (2017). The CMP approach addresses the skill of identifying the components of systems (which we consider as causes;[1] Penzlin et al., 2022) and their relationships by emphasizing whether they are linked by mechanisms. Furthermore, the CMP approach addresses cross-level reasoning by emphasizing whether causes and mechanisms refer to micro- or macro-levels of biological organization (Hmelo-Silver et al., 2017; Snapir et al., 2017).

2.4. Research about abductive reasoning in modeling for scientific inquiry

The role of abductive reasoning in scientific inquiry has been justified by theoretical and historical argumentation. Philosophers of science argue that revolutionary scientific ideas, such as Kepler's model of elliptic planet orbits or Darwin's theory of biological evolution, emerged by abductive reasoning, which means the generation and selection of novel explanations that expand what is already known about a natural phenomenon (Wirth, 2003; Schurz, 2008; Lawson, 2010; Adúriz-Bravo and González Galli, 2022). Since in modeling for inquiry a model is constructed as a possible explanation for a phenomenon (Rohwer and Rice, 2016; Rice et al., 2019), it has been argued that "the primary mode of reasoning during model construction is abductive" (Svoboda and Passmore, 2013, p. 124). By analyzing historical episodes of mathematical model construction, Park and Lee (2018) assign an abductive nature to mathematical modeling that leads to new models that are applied subsequently in mathematical inquiry. In case studies with pre-service elementary school teachers, Oh (2019, 2022) provides empirical evidence about abductive reasoning in modeling of geoscientific phenomena. The author states that the participants struggle to generate a plausible explanation if they search for a linear and direct relationship between a single cause and the observed phenomenon. Oh (2022) concludes that abductive reasoning is well-suited to the construction of models that explain phenomena in earth science if abductive reasoning is combined with systems thinking skills. Based on case studies with middle- and high-school students who constructed models for physical and biological phenomena, Clement (2008) argues that abductive reasoning is present in model construction, i.e., when modelers rely on analogies when generating explanations. This analogical reasoning connects to the pattern of creative abduction suggested by Schurz (2008, see Chapter 2.2). Svoboda and Passmore (2013) explicitly describe the usage of the selective abduction pattern during biological model construction in their article about modeling strategies among undergraduate biology students. They also describe how students apply creative abduction when generating models to explain phenomena by using analogies. The case studies of Clement (2008) and Svoboda and Passmore (2013) provide evidence that indicates the important role of abductive reasoning in modeling of biological phenomena.

In these related studies, the authors define abductive reasoning broadly as the reasoning that leads to the generation and selection of causal explanations for so-far-unexplained phenomena. In this article, we add to these studies by applying concrete theoretical concepts to operationalize abductive reasoning. These concepts are the proposed steps from the cognitive psychological framework of abduction (Johnson and Krems, 2001) and the patterns of creative and selective abduction as proposed by philosophers of science (e.g., Schurz, 2008). Furthermore, we aim to examine the relationship of these abductive reasoning concepts to the ability to model biological phenomena as complex systems.

Our research questions (RQ) are:

RQ1: To what extent are the steps of abductive reasoning present in modeling processes to explain biological phenomena?

RQ2: What are the differences between patterns of selective abduction and creative abduction when modeling biological phenomena?

RQ3: How do steps and patterns of abductive reasoning relate to modeling of biological phenomena as complex systems?

3. Methods

3.1. Study type and sample

This study investigated abductive reasoning in modeling and its relation to modeling of biological phenomena as complex systems. Participants were 20 pre-service biology teachers (mean age = 27, SD = 2.6) from master's programs at two German universities. Participants were recruited in university seminars and confirmed their intention to voluntarily participate in this study via email before the interviews.

Using modeling for inquiry is challenging for both students and teachers (e.g., Cheng et al., 2021; Göhner et al., 2022). Therefore, the inclusion criterion for the participants in this study was that they had completed a course on scientific inquiry methods. In this course, they learned about using modeling as a method for inquiry, such as constructing models based on evidence or using a model to predict a phenomenon. Although they most likely engaged intuitively in abductive reasoning during modeling activities as part of the seminar, they were not explicitly taught about the concept of abduction. This allowed the examination of abductive reasoning in modeling biological phenomena for inquiry among individuals who had learned how to use modeling for inquiry without having been explicitly taught about abductive reasoning.

1 The CMP approach has been applied to assess how learners describe complex systems (Hmelo-Silver et al., 2017; Snapir et al., 2017). In the systems thinking literature, and under the CMP approach, the term "component" is commonly used to describe entities in a system's explanation (e.g., Goldstone and Wilensky, 2008; Ben Zvi Assaraf and Knippels, 2022). However, in this study, we apply the CMP approach to modeling for inquiry, which aims to explain the emergence of a phenomenon. In the context of scientific inquiry, the term "cause" is used to describe the initial entity that leads to the emergence of the phenomenon. Therefore, in this article, we use the term "cause" instead of "component" when applying the CMP approach to modeling for inquiry.

3.2. Implementation of the modeling task

To analyze abductive reasoning processes in modeling, think-aloud interviews (Ericsson and Simon, 1980) were conducted; these were implemented online due to the pandemic situation in the winter of 2021. During the interviews, participants worked on a modeling task implemented in *SageModeler* (Bielik et al., 2018), which is an online application that allows learners to be engaged in several modeling activities from the drawing of simple diagrams to the construction of semi-quantitative simulation models. In our study, SageModeler was used as a drawing tool for creating process diagrams, enabling participants to create and label boxes and arrows. The more advanced features of the program, e.g., performing semi-quantitative simulations, were not needed for our study. Therefore, these features were not introduced to the participants and were disabled in the settings section of the SageModeler online environment. We chose SageModeler as the drawing tool for this study because it allows the drawing of process diagrams on a computer. Thus, it was a solution to enable monitoring of the drawing processes, even in an online interview situation. Additionally, we had prior experience in using this tool for drawing diagrams in previous studies with pre-service science teachers. In those studies, we found that SageModeler had good usability for a task that requires the drawing of process diagrams (Engelschalt et al., 2023).

The instruction for the modeling task given to the participants was "Draw your solution process of *how* a specific phenomenon has emerged in a process diagram while referring to concrete causes."

Abductive reasoning in model construction is about generating a causal explanation for a phenomenon. Causal explanations in science ideally include causes and mechanisms (Salmon, 1990; Alameh et al., 2022; Penzlin et al., 2022). By prompting the participants to find concrete causes and elaborate on *how* the phenomenon emerged, this instruction referred to both generating causes and mechanisms to explain a phenomenon and was applied to operationalize abductive reasoning processes in model construction. This instruction was also open for the participants to develop strategies to test their explanations; this corresponds to Johnson and Krems's (2001) *test* step, which according to our conception indicates the transition from abductive reasoning in model construction to deductive reasoning in model application.

Drawing their solution process in a process diagram was implemented as a way to scaffold participants' mental modeling activities. Furthermore, the models and modeling processes thereby externalized were analyzed regarding their complexity by applying the CMP approach (see Section Complexity in model construction processes). Examples of the process diagrams produced can be found in Figures 1A, B.

Two biological phenomena were chosen as contexts for the task. One phenomenon concerned a person with a reddened face (the reddened face phenomenon, RFP). The other concerned a male clownfish changing its sex after the only female fish in the population died (the clownfish phenomenon, CFP). We applied these phenomena to operationalize the patterns of abduction. Specifically, the RFP is relevant to participants' daily lives and most participants likely have personal experience with it. Therefore, we expected participants to know about explanations or at least causes for a person's reddened face. This argumentation is also supported by the findings of a previous study in which we implemented the RFP modeling task with pre-service science teachers and most participants generated multiple explanations for the phenomenon (see Upmeier zu Belzen et al., 2021). Thus, the RFP was used to operationalize the pattern of selective abduction (Schurz, 2008). On the other hand, as the CFP is a very specific biological phenomenon, we did not expect that most of the participants would know of an explanation for it. Given this, model construction for the CFP is about creating a plausible explanatory model by transferring knowledge from other contexts and the challenge is more to find a possible explanation meeting the given constraints. Thus, the CFP was applied to operationalize the pattern of creative abduction (Schurz, 2008). In this way, the patterns of abduction were operationalized by applying two phenomena as modeling contexts: in the RFP context, participants were expected to know about explanations or at least concrete causes, while in the CFP context, participants were not expected to have such knowledge. To ensure this difference in the modeling contexts, we excluded participants from the analysis if they reported in the think-aloud interview that they already knew about a specific explanation for the CFP or if they reported not knowing of explanations for the RFP (see Section Data processing). To generate more detailed evidence on participants' prior knowledge about explanations for the RFP and CFP, pre-tests could have been performed. Like other studies assessing knowledge and reasoning processes involved in modeling (Ruppert et al., 2017; Bennett et al., 2020), we decided against pre-testing our participants' prior knowledge about explanations for the CFP and RFP. We justify this with three arguments:

1. There are many causes to explain the RFP, and anticipation of all knowledge that is related to these causes is neither economic nor possible to fully achieve in a pre-test.
2. Prompts employed in prior knowledge pre-tests could have possibly influenced which knowledge participants would refer to, which would make their responses to the modeling task less spontaneous and less authentic.
3. Think-aloud interviews as conducted for this study are linked to high cognitive load and fatigue among the participants (Sandmann, 2014). Answering a knowledge pre-test before the interview could enhance cognitive load and fatigue.

3.3. Interview method

Participants were interviewed using the think-aloud method (Ericsson and Simon, 1980; Sandmann, 2014). Under this method, participants were asked to speak out loud about any thoughts that came into their minds while working on the modeling task. The method of think-aloud has been shown to capture reasoning processes (Sandmann, 2014; Leighton, 2017). Matching this, think-aloud has been implemented in previous studies examining pre-service science teachers' (Meister et al., 2021; Göhner et al., 2022) and high-school students' (Meister and Upmeier zu Belzen, 2020) reasoning processes in modeling for inquiry. The structure of the interviews followed the suggestion by Sandmann (2014): after a short introduction about the aim of the interview and an explanation of the think-aloud method, participants started with

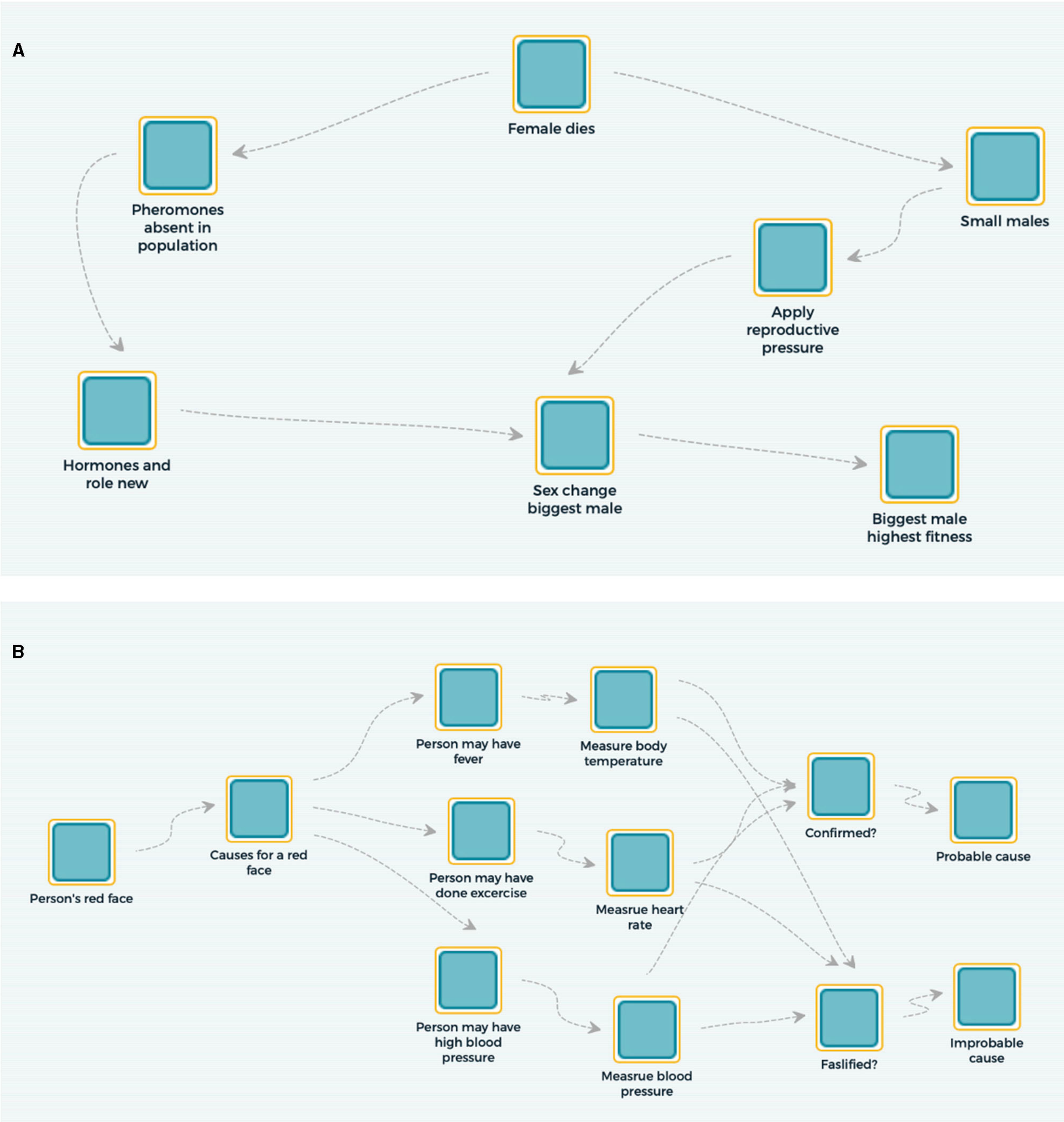

FIGURE 1
Examples process diagrams by **(A)** participant CFP08 and **(B)** participant RFP05. While participant CFP05 referred to causes and mechanisms that might explain the CFP, RFP05 referred only to causes that might explain the RFP but additionally added strategies to test the causes.

a warm-up task to get used to speaking every thought out loud. In this study, the warm-up task was to formulate a heading for a short picture story. Before working on the modeling task, each participant watched a short video (1:42 min) that explained how to draw a process diagram in *SageModeler*. After watching the video, either the RFP or the CFP was randomly presented to the participant in the form of a short text to read. Randomization was automatically implemented in SoSci Survey. While the participant worked on the modeling task (either the CFP or the RFP modeling task), the interviewer did not comment on their thoughts. The interviewer only replied to questions from the participant that concerned their general understanding of the instruction. If a participant asked specific questions about the phenomena, the interviewer did not answer them concretely and just referred to the task. On average, the interviews lasted around 21 min each (M = 20.87 min, SD = 5.7 min).

3.4. Data processing

The audio of the interviews and the screens of the interviewed participants were recorded. The audio was transcribed. Furthermore, the process diagrams produced were collected via a shared link. Two participants were excluded from the analysis. One was excluded since the participant (pseudonym CFP01) stated that they already knew of an explanation for the CFP. Therefore, the participant had explicit prior knowledge about the CFP, which does not match the definition of creative abduction (Schurz, 2008). The other participant (pseudonym RFP09) modeled the RFP and was excluded due to not being able to produce a process diagram in *SageModeler*, which inhibited this participant's progression in the task.

3.5. Data analysis

3.5.1. Abductive reasoning steps

To analyze participants' engagement in abductive reasoning steps during model construction, a coding scheme was developed based on Johnson and Krems (2001, Table 2). In the development process, the steps *collect data* and *comprehend* were adapted from their original descriptions. This was necessary due to differences in the task format. In contrast to our task, the task used in the study by Johnson and Krems (2001) allowed the participants to always collect additional data, which they needed to comprehend. While in Johnson and Krems's framework *collect data* was about actively generating data and *comprehend* was about understanding the collected data, in our study *collect data* was about explicating ideas on how to generate data and *comprehend* was about understanding the data that were given in the modeling task instruction.

The *test* step, which is another step in Johnson and Krems's framework of abduction, was used to operationalize the transition from abductive reasoning in model construction to deductive reasoning in model application in this study.

The coding scheme shown in Table 2 was used to identify the abductive reasoning steps in the transcripts of the interviews. Coding was performed using the MAXQDA program (VERBI Software, 2022), which allowed coders to watch recorded videos while coding passages from the transcripts. Coders were instructed to assign codes to related passages that were as short as possible but as long as necessary. Therefore, passages of varying lengths (from small word groups to several sentences) were assigned to the steps. Passages that did not fit into any of the steps (such as when participants talked about how they arranged their diagram) were not coded. The reliability and objectivity of the analysis were supported by substantial intra-rater agreements for two transcripts (k = 0.73, calculated according to Brennan and Prediger, 1981; interpreted according to Landis and Koch, 1977) and substantial inter-rater agreements between two coders for six transcripts (k = 0.71, Landis and Koch, 1977). Agreement was counted if at least 95% of a passage received the same code from the two independent coders.

Referring to RQ1, the occurrence and frequency of each of the steps were analyzed. This was done by examining which of the steps occurred in each participant's transcript and how often they occurred. By counting occurrences of each step, we gathered information about how often a step occurred in modeling processes for each participant and overall for the 18 participants whose data were analyzed.

Referring to RQ2, frequencies of the abductive reasoning steps addressed were compared between CFP participants and RFP participants to examine possible differences between the modeling processes.

3.5.2. Complexity in model construction processes

In modeling for inquiry, models are constructed as explanations for phenomena (Rice et al., 2019; Upmeier zu Belzen et al., 2021). If this explanation involves causes and mechanisms on different organizational levels, the phenomenon is explained as a complex system. However, modelers are not always able to formulate mechanisms. In such cases, phenomena are only explained by a cause. This is why, for our analysis, we defined a model as an attempt to explain the phenomenon that includes at least one concrete cause for its emergence.

Both implemented phenomena, the RFP and CFP, refer to physiological processes within an organism as well as the interplay of an organism with the environment. Thus, they can be explained as complex systems (Hmelo-Silver et al., 2017; Snapir et al., 2017). Our task instruction allowed the participants to suggest several concurring models for the same phenomenon. Therefore, we did not analyze the complexity of single models but all models that participants proposed in their model construction processes. Participants' model construction processes were analyzed discursively in terms of complexity by two coders who analyzed the diagrams in combination with the think-aloud protocols. Therefore, a coding scheme was adapted based on the CMP approach (Hmelo-Silver et al., 2017). The approach scores complexity based on connections between causes (C, originally labeled *components* by Hmelo-Silver et al., 2017, see Chapter 2.3), mechanisms (M), and the phenomenon (P) in the CMP score and the connection of micro- and macro-levels of organization in the micro–macro score.

The adaptation of the scheme for our study mainly involved changes in the CMP score. In the study of Hmelo-Silver et al. (2017), participants were instructed to model a lake ecosystem. The participants received points for describing concrete phenomena within their externalized models. The instruction of our study differed from the study of Hmelo-Silver et al. (2017) in that our participants were explicitly prompted to find causes for a given phenomenon (the RFP or CFP). Therefore, a concrete phenomenon was described in the instruction, and only representing this description in the instruction was not scored ("P," Table 3). Participants who generated only one cause, which they directly connected to the emergence of the phenomenon ("$C \rightarrow P$"), generated a simple linear explanation that is most likely not adequate for explaining biological phenomena (Haskel-Ittah, 2022). Participants who generated multiple causes ($|{:}C \rightarrow P{:}|$) showed higher complexity in their model construction processes, because this indicates that they acknowledged the presence of more than one entity that might cause a phenomenon. However,

TABLE 2 Coding scheme for analyzing abductive reasoning steps.

Code	Coding rules participant…	Example
Collect data	… develops ideas on how to generate data without referring to concrete explanations or claims that more information is needed to start solving the phenomenon.	The first thing I do is, when the person enters, I look at him or her and try to find some indications on his or her body.
Comprehend	… activates prior knowledge to understand the given data of the instruction or reports difficulties in understanding the given data of the instruction.	Okay, so, when the female dies, then somehow some kind of communication process must take place. Okay, the question now, how can the fish suddenly change its sex?
Refine	… specifies generated explanations.	Maybe it is not only the presence of hormones (…) Perhaps some sort of threshold needs to be reached as well.
Check	… evaluates plausibility/probability of thought-up explanation.	My idea was that the person did sports (…) that seems logical to me.
Discriminate	… decides against an explanation if it was not evaluated as plausible or if others were more plausible.	I guess he did <u>not</u> paint himself, it is more likely a body reaction.
Resolve anomaly	… discards (parts of) generated explanations.	Something else is happening here. So, I'd like to change that again.
Test*	… derives a prediction from a generated explanation or derives a strategy for how to test the generated explanation.	If I want to examine whether doing exercise is the cause, I could measure heart rate.

*According to our conceptualization of modeling for inquiry, the "test" step represents the transition from abductive reasoning in model construction to deductive reasoning in model application.

TABLE 3 Coding scheme for CMP scoring of model construction processes.

CMP relation	Explanation	Score
P	Participants described the phenomenon without elaborating on causes and mechanisms for its emergence. Example RFP: *No examples in our data* Example CFP: *Female of the population dies → biggest male fish changes sex → new female*	0
C→ P	Participants generated a single cause to explain the phenomenon without elaborating on mechanisms by which this cause might lead to the phenomenon. Example RFP: *Anger—causes→ reddened face* Example CFP: Hormones—*influence→ sex change*	1
|:C→P:|	Participants guessed multiple causes to explain the phenomenon without elaborating on mechanisms by which the causes might lead to the phenomenon.	2
C→M→P	Participants guessed a single cause to explain the phenomenon and elaborated on a mechanism by which the cause might lead to the phenomenon. Example RFP: *A stress situation—leads to → secretion of stress hormones—body reaction of→ increasing blood pressure—higher blood flow in the head—results in → the reddened face* Example CFP: *Absence of female fish —lack of pheromone changes→ hormonal system of the male fish—leads to → sex change.*	3
|:C→ M→ P:|	Participants guessed multiple causes to explain the phenomenon and elaborated on mechanisms by which the causes might lead to the phenomenon.	4

only when they included at least one cause and a mechanism to explain the phenomenon had participants explained it as a complex system. Participants who connected several causes and mechanisms to explain the phenomenon ("|:*C→M→P*:|") demonstrated the highest levels of complexity in their model construction processes. This indicates that they recognized that multiple entities in a system can cause a biological phenomenon and that there are hidden mechanisms that lead to the emergence of biological phenomena. Within the coding scheme, causes were defined as the initial entity for *why* the phenomenon emerged (Kampourakis and Niebert, 2018) and mechanisms were defined as the entity's activities and interactions describing *how* the phenomenon emerged (Craver and Darden, 2013; Haskel-Ittah, 2022). Direct arrows from cause to phenomenon without any descriptions or arrows containing verbal connection that include only vague filler terms such as *influence, affect,* and *lead to* (*black boxes,* Haskel-Ittah, 2022) were not counted as concrete mechanisms and thus not scored under our scheme. Technical terms summarizing concrete biological mechanisms such as *natural selection* or *blood vessel dilation* were coded as mechanisms.

The coding scheme for the micro–macro score was adopted from Hmelo-Silver et al. (2017). The lowest micro–macro scores were coded when participants only referred to either the micro- or macro-level of biological organization (Table 4). The highest scores were coded when participants connected elements on both the micro- and macro-levels during model construction. The latter indicates that participants took the complexity of biological organization into account.

The micro-level refers to "the part of reality that is only accessible through the use of science-based technologies such as microscopes" (see *microcosm*, Schneeweiß and Gropengießer, 2022,

TABLE 4 Coding scheme for analyzing micro–macro relationships in model construction processes.

Micro/Macro relationship	Explanation	Score
Micro/Macro	Participants refer to causes or mechanisms either on macro-level or on micro-level only Example RK: *Anger—causes→ reddened face* Example CF: Need for reproduction→ *sex change*	1
Micro+Macro	Participants refer to causes or mechanisms on macro-level and micro-level, without elaborating on their connection Example RK: *Pigments → reddened face* Example CF: *Chromosomes → sex change*	2
Micro⇌Macro	Participants link causes and mechanisms on macro- and micro-level Example RK: *A stress situation —leads to → secretion of stress hormones—body reaction of → increasing blood pressure—higher blood flow in the head—results in → the reddened face* Example CF: A*bsence of female fish lack of pheromone changes → hormonal system of the male fish —leads to → sex change*	3

p. 145), which are parts on the cell level and below (Hmelo-Silver et al., 2017; Schneeweiß and Gropengießer, 2022). Parts on the tissue level and above (e.g., organisms and populations) were considered as macro-level entities (see *mesocosm* and *macrocosm*, Schneeweiß and Gropengießer, 2022). Emotions such as *anger* or *shame* were scored as macro-level causes for the RFP, since they are reactions of a person (organism) to a specific situation.

Referring to RQ3, the relationship between abductive reasoning patterns and complexity, as along with the relationship between the abductive reasoning steps and complexity, was examined. Specifically, the relationship between complexity in model construction and abductive reasoning patterns was analyzed by comparing how many participants achieved high scores in CMP (scores of 3 and 4) and micro–macro (score of 3) for the RFP (selective abduction) and the CFP (creative abduction). To investigate possible relationships between the complexity of generated models and abductive reasoning steps, we analyzed whether frequent engagement in abductive reasoning steps correlated with CMP and micro–macro scores. Therefore, the frequency of abductive reasoning steps that each participant engaged in was counted. Subsequently, Spearman's correlation coefficients (Field, 2013) between the frequency of engagement in abductive steps and complexity scores (CMP score and micro–macro score) were calculated.

4. Results

4.1. RQ1: abductive reasoning steps in biological model construction

In this study, we applied Johnson and Krems's (2001) framework to operationalize cognitive processes in abductive reasoning with six steps that were analyzed by a coding scheme. Analysis showed that all six steps were present in the modeling processes of our 18 participants (Table 5). According to our coding, abductive reasoning steps occurred approximately 9 times ($M = 9.33$, $SD = 6.12$) in the model construction processes of each participant. However, only the *comprehend* step was found in the transcripts of all participants. Although the *refine* and *check* steps were coded frequently, in most of the transcripts, the *collect data* and *discriminate* steps were coded rarely. The step *resolve anomaly* was coded once and independently by the two coders at the same position in the relevant transcript.

4.2. RQ2: comparison of creative and selective abduction

We applied the CFP to operationalize the pattern of creative abduction and the RFP to operationalize the pattern of selective abduction. While the frequencies of *refine*, *check,* and *discriminate* were similar between the modeling processes for the CFP and the RFP (Table 5), we found five differences between the phenomena.

1. Presence of collect data. The collect data step was found in the modeling processes of the RFP, but not the CFP. The code appeared when participants explicated strategies for how to examine the phenomenon generally, without explicit assumptions, and mostly (in all but one case) before participants explicated a model for explaining the phenomenon.

> *"First of all, of course, I would examine the room, yes observe the room, I'll write 'observe the room'. Then I would look if I found things or objects that explain the problem or the red face."* (Think-aloud transcript of RFP06, passage related to the code *collect data*, at the beginning of the transcript).

2. Initiation of the modeling process. While all CFP participants started their model construction with comprehend, this was only the case for four participants modeling the RFP. Three participants modeling the RFP explicated strategies referring to collect data first and two participants started immediately with the generation of models for the RFP. On average, CFP participants needed a longer period of time before they generated their first primary model to explain the phenomenon than RFP participants (Figure 2). As an extreme example, participant CFP09 only represented the information given by the instruction in the diagram and thus did not generate any model for the CFP. The participant finished the task by claiming not to be able to produce a better solution due to a lack of knowledge of clownfish.

TABLE 5 Frequency of coded abductive reasoning steps and number of participants who referred to them when modeling the CFP or RFP.

Code	Frequency of codes			Number of participants		
	CFP	RFP	Total	CFP	RFP	Total
Collect data	0	7	7	0	4	4
Comprehend	29	24	53	9	9	18
Refine	25	21	46	9	7	15
Check	37	18	55	8	8	16
Discriminate	3	3	6	3	2	5
Resolve anomaly	1	0	1	1	0	1
Test*	6	12	18	2	6	8

*According to our conceptualization, the "test" step represents the transition from abductive reasoning in model construction to deductive reasoning in model application.

3. Proposal of alternative models. For both phenomena, most participants generated at least two alternative models for their phenomenon (8 out of 9 for the RFP; 6 out of 9 for the CFP). However, while CFP participants worked longer on one generated model by checking its plausibility and refining it, participants modeling the RFP often continued in their modeling process by proposing alternative models to explain the RFP immediately. This was observed 13 times in the modeling processes of five RFP participants, as illustrated by the following quote, where three models to explain the RFP are generated immediately:

> *"Exercise is a possible explanation for the reddened face. I write down 'Person may have done exercise'. The person could also have a fever [...] I write down 'Person may have fever'. Or the person could also deal with high blood pressure."* (Think-aloud transcript of RFP03, underlined passages are first primary models to explain the RFP).

4. Plausibility check of generated models. A plausibility check of generated models was found more often for the CFP ($n = 37$) than for the RFP ($n = 18$). Within the passages that were coded as check, participants modeling the CFP reported uncertainty about their models, as illustrated by this quote:

> *"I am uncertain if I have taken the right path, so I am going through it again. The phenomenon is: [...] The female dies, the strongest male turns back into a female, and the same clownfish population is created. [...] I assume it could be death, which is related to the absence of certain hormones that are no longer released. Whether it has to do with fish perception, I am unsure, but it does somehow result in a change in gene expression."* (Think-aloud transcript of CFP06, passage related to the code *check*).

Furthermore, the uncertainty of CFP participants was frequently linked to vague explanations in combination with the explication of lacking specific prior knowledge about clownfish:

> "The female changes something in the environment [...]. So, it is not about other living beings. I do not know anything about clownfish. [The female clownfish] can send any information somehow into the water" (Think-aloud transcript of CFP02, passage related to the code *check*).

Plausibility *checks* in RFP modeling processes were less frequent ($n = 18$), and seldom linked to uncertainty and vague formulations. In contrast, participants referred to prior experiences from their everyday lives to justify the plausibility of their generated models:

> "Nervosity makes sense. My best friend, for example, always blushed extremely when she had to present something in front of the class" (Think-aloud transcript of RFP01, passage related to the code *check*).

5. Although the focus of our study was on examining abductive reasoning in modeling, the fifth examined difference relates not only to abductive reasoning in model construction but moreover to the transition from abductive reasoning in model construction to deductive reasoning in model application. In our study, the transition to model application was operationalized by Johnson and Krems's (2001) *test* step, when strategies on how to investigate generated explanations were developed. *Test* was coded 18 times for eight of the 18 participants. It was considered twice as often for the RFP ($n = 12$, from six participants) as for the CFP ($n = 6$, from two participants).

> *"If I want to examine whether doing exercise is the cause, I could measure heart rate."* (Think-aloud transcript of RFP05, passage related to the code test. RFP05 also included testing strategies in the generated process diagram, see Figure 1B).

4.3. RQ3: relationship between abductive reasoning and modeling of phenomena as complex systems

We operationalized the extent to which participants modeled the phenomena as complex systems by examining CMP and micro–macro relations, as proposed by Hmelo-Silver et al. (2017). Participants achieved an average CMP score

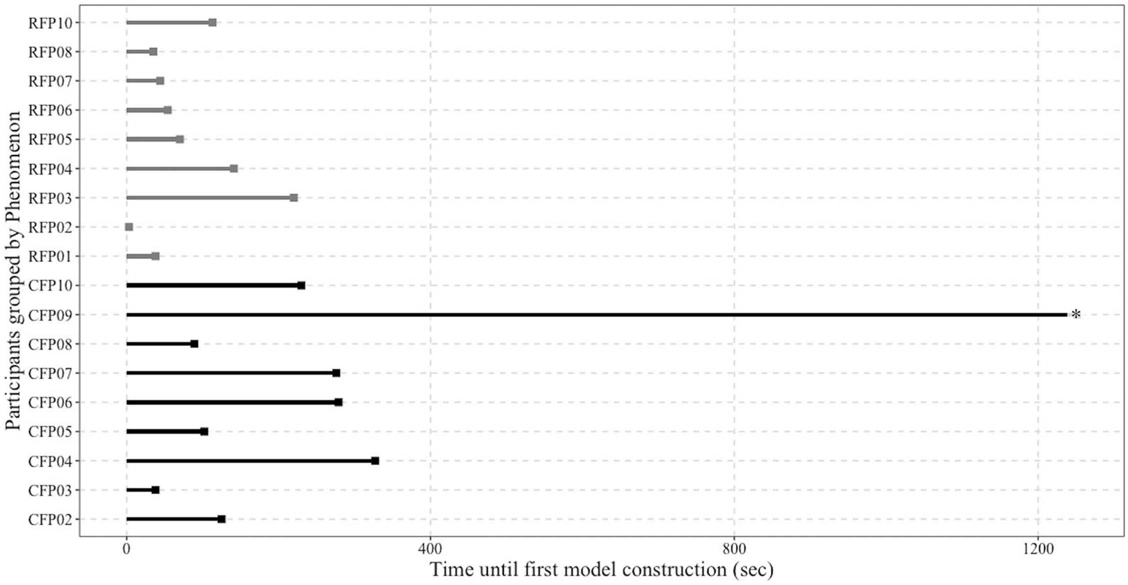

FIGURE 2
Amount of time that every participant needed to generate an initial explanatory model for the phenomenon*. *Participant CFP09 did not produce a model to explain the phenomenon. Participants RFP09 and CFP01 were excluded from the analysis (see Section Data processing).

of 2.72 ($SD = 1.23$) and an average micro–macro score of 2.20 ($SD = 0.97$).

We found a significantly strong correlation between the frequency of abductive reasoning steps and CMP score ($r = 0.52$, $p < 0.05$; Cohen, 1988, Figure 3). On the level of concrete steps, significant correlations were found between the CMP score and the frequency of *refine* ($r = 0.48$, $p < 0.05$) and *check* ($r = 0.51$, $p < 0.05$). However, no correlation was found between the frequency of abductive reasoning steps and the micro–macro score (Figure 2).

Referring to both CMP and micro–macro scores, CFP participants addressed higher complexity in their model construction processes than RFP participants (Table 6). While most of the CFP participants achieved the highest scores for complexity regarding CMP relations (5 out of 9) and micro–macro relations (6 out of 9), this was only the case for two of the nine CFP participants.

It is also notable that six of the eight participants who transitioned from model construction to model application by developing strategies to test their explanations showed a low CMP score (all six received a CMP score of 1) and a low micro–macro score (five participants received a micro–macro score of 1 and one participant received a micro–macro score of 2). Thus, only two participants developed strategies to test generated explanations and received high complexity scores for model construction (a CMP score of 3 or 4 and a micro–macro score of 3). Both participants modeled the CFP.

5. Discussion

5.1. RQ1: abductive reasoning steps in biological model construction

Johnson and Krems (2001) stated that abductive reasoning processes do not always include all proposed steps. Congruently with this, we observed some steps more frequently than others. The steps *collect data*, *discriminate,* and *resolve anomaly* were only found rarely in the modeling processes of this study's participants. However, this does not necessarily indicate that these steps are not important in biological model construction, since their rare presence is probably explained by the limitations of this study's modeling task format. For instance, to be able to *collect data,* it is important to observe the phenomenon (Greve and Wentura, 1997; Constantinou, 1999). This was hardly possible in the modeling task of our study. Participants could only use information about the phenomenon that was given to them in the instruction to explicate ideas on how they might collect data.

Hence, *comprehend, refine,* and *check* were frequently found in the modeling processes in our study, and this indicates the important role of these steps in model construction for biological phenomena. We assume that the steps *collect data, discriminate*, and *resolve anomaly*, which we rarely found in our data, are also involved in model construction for biological phenomena. For instance, studies with more interactive modeling tasks have shown that collecting data is an important part of modeling for inquiry (e.g., Constantinou, 1999; Meister et al., 2021).

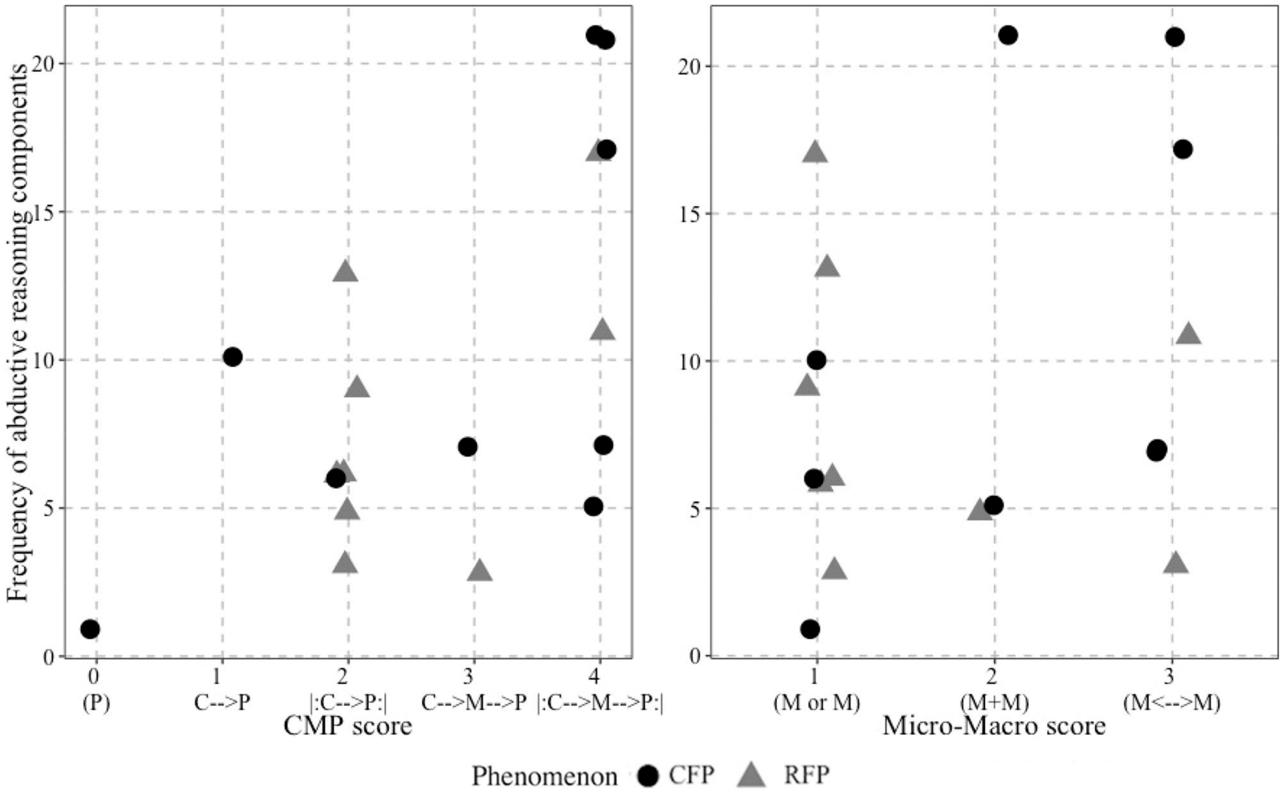

FIGURE 3
Distribution of participants' CMP scores (left) and micro-macro scores (right) in relation to the frequency of abductive reasoning steps that occurred in their modeling processes.

5.2. RQ2: comparison of creative and selective abduction

The pattern of abduction that is applied in model construction depends on the extent to which modelers already know about possible explanations for a phenomenon (Schurz, 2008). For operationalization of creative abduction, we applied the CFP as a modeling context in which participants did not know of explanations. For operationalization of selective abduction, we applied the RFP as a modeling context in which participants knew of explanations, e.g., from their everyday lives and individual experiences with the phenomenon. The findings that CFP participants explicated lacking knowledge and RFP participants referred to concrete examples from everyday life during their model construction support this methodological operationalization. Moreover, we identified five differences between the modeling processes of the CFP and the RFP, which is consistent with previous research suggesting that engagement in the modeling process is context-dependent (Svoboda and Passmore, 2013; Bennett et al., 2020; Schwarz et al., 2022).

The first difference examined relates to participants' wishes and ideas to *collect data*, only found in RFP modeling processes. This may be interpreted as a wish to obtain evidence to be able to select between possible alternatives in selective abduction. However, the format of the task did not allow the participants to collect new data about the phenomena, which might have inhibited them from discriminating between generated explanations based on data. Thus, this limitation of the modeling task might also explain the infrequent occurrence of *discriminate,* especially in modeling processes for the RFP, in which most participants generated concurring models.

The second difference examined was about the initiation of model construction: while all RFP participants generated their

TABLE 6 Distribution of participants' complexity scores for model construction for CFP and RFP.

	CFP (*n*)	RFP (*n*)
CMP score		
4 |:C−>M−>P:|	5	2
3 C−>M−>P	1	1
2 |:C−>P:|	1	6
1 C−>P	1	0
0 P	1	0
Micro−Macro score		
3 M< − >M	4	2
2 M+M	3	1
1 M or M	2	6

first explanatory model relatively quickly—two participants started generating models right away—all CFP participants began with an attempt to *comprehend* the phenomenon at first and needed more time to construct a (primary) explanatory model. The observation that learners spend a great deal of time comprehending what is going on when they construct models for phenomena that they do not know much about is also reported by other scholars (e.g., Bierema et al., 2017; Schwarz et al., 2022). Participant CFP09 only engaged in the *comprehend* step and did not generate a plausible model. This example illustrates how a lack of knowledge about a phenomenon and the inability to create analogies inhibit model construction in such a way that no plausible explanation for a phenomenon can be generated (Göhner and Krell, 2020; Göhner et al., 2022). We interpret the differences in initial model construction (i.e., longer time spent comprehending the CFP compared to the quick generation of explanatory models for the RFP) as indicators of higher difficulty in constructing explanatory models for the CFP than for the RFP. This is also supported by the third and fourth differences examined (RFP participants generated alternative models more quickly than CFP participants, and CFP participants checked their generated models for internal consistency more often than RFP participants did).

The fifth difference was that RFP participants engaged more frequently in the *test* step than CFP participants. Thus, RFP participants transitioned more often from generating explanations in model construction to testing explanatory model applications. This result might indicate that developing strategies to test generated models is easier when modelers can rely on explanations from their prior knowledge. This connects to studies in the field of experimental competencies stating that prior contextual knowledge influences students' ability to plan experiments for scientific inquiry (Schwichow and Nehring, 2018). To illustrate this argument with examples from this study's modeling contexts, it seems easier to develop testing strategies to determine whether a person's reddened face is caused by exposure to the sun or alcohol abuse than to develop strategies for testing whether the sex change of a male clownfish is caused by the absence of female pheromones. This supports argumentation from Schwarz et al. (2022), who argue that "the more a person or group 'knows' about the phenomena [. . .], the more they can do within that modeling context." (p. 1,091). Another explanation for the fact that CFP participants engaged less frequently in the *test* step can be derived from the result that they needed more time to generate their models. Although there was no time limit for the interviews, constructing plausible models for the CFP was time-consuming (Figure 3) and thus might have been mentally exhausting. As a result, participants may have eventually become cognitively fatigued and lost further motivation to derive strategies to test their generated models.

5.3. RQ3: relationship between abductive reasoning and modeling of phenomena as complex systems

Model construction is about generating a plausible explanation for a phenomenon (e.g., Upmeier zu Belzen et al., 2021; Adúriz-Bravo and González Galli, 2022). Phenomena are explained as complex systems if their explanations include causes and mechanisms on different organizational levels (Schneeweiß and Gropengießer, 2019, 2022; Penzlin et al., 2022). In this study, we analyzed the complexity of model construction processes determining the extent to which participants explain a phenomenon as a complex system during model construction. Therefore, we applied the CMP approach of Hmelo-Silver et al. (2017) to evaluate the extent to which participants linked causes and mechanisms to explain a phenomenon (CMP score) and the extent to which they linked micro and macro levels of biological organization (micro–macro score).

Adúriz-Bravo and González Galli (2022) assumed that the complexity of initial generated explanations will be low as a result of individuals staying close to intuitive formulations and will probably increase during the process of abductive reasoning in model construction. The significant correlation between frequencies of abductive reasoning steps with CMP scores supports this assumption, by indicating that extensive abductive reasoning in model construction is related to the connection of causes and mechanisms to explain the phenomenon in model construction. However, no correlations were found between the frequency of abductive reasoning steps and the micro–macro score. This implies that extensive abductive reasoning does not necessarily lead to the connection of macro and micro levels, which indicates that abductive reasoning alone is not enough to explain phenomena as complex systems in biological model construction. We assume that an interplay between abductive reasoning and systems thinking skills, such as cross-level reasoning (Tamir et al., 2023), is necessary for explaining biological phenomena as complex systems in model construction. This idea has also been proposed in the field of earth science education by Oh (2019, 2022). On the other hand, with respect to the large number of different organizational levels that can be addressed when generating biological explanations (Schneeweiß and Gropengießer, 2019, 2022), the distinction between micro- and macro-levels as suggested by the CMP approach (Hmelo-Silver et al., 2017) could fall short to examine a possible relationship with abductive reasoning steps. Consequently, it might be powerful to consider a more fine-grained analysis of the organizational levels addressed, and how they are connected in the interplay of cause, mechanism, and phenomenon, as was done in the study by Penzlin et al. (2022).

In addition to connecting causes and mechanisms on different organizational levels, the systems thinking literature suggests that further skills need to be applied to explain phenomena as a complex system. Among others, these skills also include developing complex mechanisms such as feedback loops or considering the system's change over time (Ben Zvi Assaraf and Knippels, 2022; Tamir et al., 2023). Future studies are needed to examine how cognitive processes of abductive reasoning, which we operationalized as the steps of abduction (Johnson and Krems, 2001), are related to further systems thinking skills.

CFP participants addressed higher complexity in their model construction processes than RFP participants according to both CMP and micro–macro scores. This indicates that participants modeling the CFP tended to explain their phenomenon as a complex system, combining causes and mechanisms across micro- and macro-levels of biological organization. In contrast, participants modeling the RFP mostly referred to simple cause-and-effect relationships in their model construction processes. We explain this by the strong everyday life relevance of the RFP. In everyday life situations, explanatory models usually do not refer to multiple causes and mechanisms on different organizational levels but to simple cause–effect relations. It is likely that the pre-service biology teachers engaged in their master's studies who participated in our study would be capable of explaining the RFP as a complex system. However, most of the RFP participants constructed simple models and transitioned to developing strategies to test them in model applications. Göhner et al. (2022) found that if modelers constructed complex models, this would not automatically lead them to engage in model application. Moreover, to transition from model construction to model application, modelers need to perceive their generated models as plausible. For our results, this might indicate that less complex models for the RFP were plausible and therefore suited to enabling the participants to move on by developing strategies to test their generated models. Since only two participants (both of whom modeled the CFP) engaged in model application and received high complexity scores, our results might suggest that addressing high complexity in model construction could stunt the transition to model application. Explaining phenomena as complex systems in model construction and developing strategies to test these complex explanations in model application are difficult tasks that require the highest level of systems thinking skills (Ben Zvi Assaraf and Knippels, 2022; Tamir et al., 2023) and modeling competencies (Upmeier zu Belzen et al., 2021). Thus, it is not surprising that only two of the 18 participants explained their phenomenon as a complex system in model construction and developed strategies to test generated explanations in model application.

6. Conclusion and outlook

An important role of abductive reasoning in modeling for inquiry in biology has been justified by historical analysis of modeling processes leading to important ideas, such as Darwin's theory of evolution (Adúriz-Bravo and González Galli, 2022), theoretical argumentations (Upmeier zu Belzen et al., 2021), and case studies (Clement, 2008; Svoboda and Passmore, 2013). With this study, we add to prior findings by applying concrete theoretical concepts to operationalize abductive reasoning in the form of the steps (Johnson and Krems, 2001) and the patterns of abduction (Schurz, 2008), and by examining their role in modeling of biological phenomena as complex systems. Our results provide evidence that the abductive reasoning steps *comprehend* (understanding the phenomenon), *check* (evaluating the plausibility of an explanation), and *refine* (specifying an explanation) are involved in model construction for biological phenomena. However, participants' frequent engagement with these steps alone did not indicate that they were explaining phenomena as complex systems. As also suggested in the field of earth science education (Oh, 2022), we assume that an interplay between abductive reasoning and systems thinking skills, such as cross-level reasoning (Tamir et al., 2023), is needed to explain biological phenomena as complex systems in model construction. Testing this assumption in future studies will require a fine-grained examination of abductively generated explanations, as in the study by Penzlin et al. (2022).

The creative pattern of abduction, as operationalized by the CFP modeling context, was associated with frequent consistency checks and high complexity in model construction. However, there were rare transitions from generating explanations in model construction to testing them in model application. This may suggest that modeling contexts in which learners need to creatively generate a novel explanation for a phenomenon do not encourage them to test the generated explanations. Nevertheless, these contexts may be suited to fostering learners' construction of complex explanatory models. On the other hand, the selective pattern of abduction, as operationalized by the RFP modeling context, was connected to rapid generation of multiple simple models and to frequent transitions from model construction to model application. This might indicate that modeling contexts in which learners already have explanations for a phenomenon may not foster learners' construction of complex models. However, such contexts could be suitable to foster learners' transition from generating explanations in model construction to testing them in model application.

The findings of this study are limited by the openness of the format of the modeling task and its small sample of 18 pre-service science teachers during their master's studies. The stated differences between creative and selective abduction operationalized by the CFP and RFP in this study need to be supported with further evidence by larger studies on pre-service teachers' modeling processes and studies that operationalize patterns of creative and selective abductive reasoning with other biological phenomena. To further investigate the other findings of this study (for instance, to examine the extent to which complexity in model construction stunts transition to model application), studies with focused modeling tasks that guide participants more during their modeling processes are needed.

Data availability statement

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

Ethics statement

In accordance with local legislation and institutional requirements, our study did not require the approval of an Ethics Committee because the research did not pose any threats or risks to the participants, and it was not associated with high physical or emotional stress. Nevertheless, it is understood, that we strictly followed ethical guidelines as well as the Declaration of Helsinki. Before taking part in our study, all participants were informed about its objectives, absolute voluntariness of participation, possibility of dropping out of participation at any time, guaranteed protection of data privacy (collection of only anonymized data), no-risk character of study participation, and contact information in case of any questions or problems. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

PE, AU, and DK: conceptualization. PE, MR, and JP: methodology, validation. PE and MR: analysis, investigation, and visualization. AU, PE, and MR: data curation. PE: writing—original draft preparation. PE, AU, JP, and DK: writing—review and editing. AU and DK: supervision. All authors contributed to the article and approved the submitted version.

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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.

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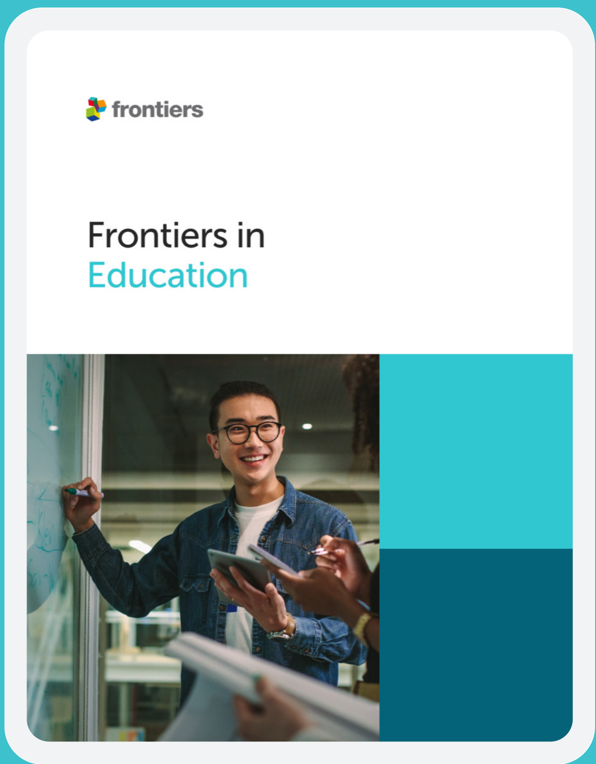

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