Meta-Theoretic Competence for Computational Agent-Based Modeling

Hillary Swanson
Utah State University
hillary.swanson@usu.edu

Uri Wilensky
Northwestern University
uri@northwestern.edu

ABSTRACT

In the U.S. context, science standards encourage educators to engage students in modeling practices, including computational modeling. While much work has investigated the productivity of computational modeling with respect to students' development of scientific content knowledge, less work has focused on students' development of knowledge and skills for participation in computational modeling practices. A first step in understanding how these practices develop is examining students' activity in the context of computational modeling environments with attention to the productive moves they make. These moves can provide insight into the knowledge they bring to their learning, which may be foundational to the development of more sophisticated engagement in computational modeling practices. This paper presents empirical results of an investigation of the knowledge one student brings to her interaction with a computational modeling microworld as she models the spread of disease.

CCS CONCEPTS

• **Social and Professional Topics**; • **Human-Centered Computing**;

KEYWORDS

Science education, Computational modeling microworlds, Metatheoretic competence

ACM Reference Format:
Hillary Swanson and Uri Wilensky. 2024. Meta-Theoretic Competence for Computational Agent-Based Modeling. In *Symposium on Learning, Design and Technology (LDT '24), June 21, 2024, Delft, Netherlands.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3663433.3663458

1 INTRODUCTION

In the U.S. context, science education has shifted from teaching students the content and skills of science separately, to helping students learn both together in an integrated way, through participation in science practices [14], [28]. The perspective at the heart of this reform is that students should construct the knowledge of a domain through participation in its knowledge-building practices [33]. Theory building is a key activity of science [36]. Recognizing its importance, the Next Generation Science Standards (NGSS) feature theory-building practices such as modeling and explanation as standards for K12 science education [27].

Modeling has been a focus of design and empirical work within science education research. Activities have been designed for engaging students in the exploration, construction, evaluation, revision, and application of different kinds of models, ranging from physical microcosms [22], [25], to drawn models illuminating causal mechanisms "a level below" [20] a phenomenon [9], [19], [23], [29], to mathematical models [21], [37]. Computational modeling is a key theory-building practice of contemporary science [15], [34], [44]. A number of research programs have developed learning environments featuring computational models. These environments support a range of activities, from exploring and modifying computational models, to building, testing, and debugging them [7], [8], [11], [12], [30], [41]. A subset of this group has designed learning environments for engaging students in computational agent-based modeling [42], [43], [45], [47], [50]. These environments support exploring, building, testing, and debugging models of agent-level interactions, to more accurately simulate the emergence of observable phenomena at the aggregate level. Computational agent-based modeling environments are designed to help students explore complex systems phenomena, from thermal equilibration to predator-prey dynamics [46], [49].

While much work has investigated the productivity of computational modeling with respect to students' development of scientific content knowledge [3], [5], [32], [46], [49], less work has focused on students' development of knowledge and skills for participation in computational modeling practices [24]. A first step in understanding how these practices develop is examining students' activity in the context of computational modeling environments with attention to the productive moves they make. These moves can provide insight into the knowledge students bring to their learning which may be foundational to the development of more sophisticated engagement in computational modeling practices. By understanding the knowledge resources that are drawn out by computational modeling environments, designers can tune modeling activities to more systematically elicit and develop these resources into expert practices.

Prior work has characterized students' productive participation in modeling practices in the context of computational modeling environments, attending to the informal knowledge and skills they leverage. This includes work documenting students' prior knowledge regarding particular phenomena [52] and work identifying the productive moves they make in computational modeling activities [39], [40]. The present work builds on this foundation, offering a high-resolution characterization of the knowledge underlying the productive moves made by one student during her construction

LDT '24, June 21, 2024, Delft, Netherlands

ACM ISBN 979-8-4007-1722-2/24/06
https://doi.org/10.1145/3663433.3663458

of an agent-based computational model. The paper ends with a discussion of how this knowledge might be intentionally drawn out and developed through the design of modeling activities.

2 THEORETICAL FOUNDATIONS

2.1 Theory-Building Games

The present work views theory-building practices, including computational modeling, through the lens of *epistemic forms and games*. Collins and Ferguson [6] characterize the knowledge-building work of scientists as epistemic games. Using the game of *tic tac toe* as an analogy, they explain how a particular epistemic form guides the play of an epistemic game. In tic tac toe, the crosshatch structure (form) dictates the possible moves a player can make and therefore the play of the game. In scientific games, scientists make moves to fill out target forms, which are templates that organize the knowledge they are building to address a particular research question or more general inquiry. In filling out the form, scientists produce a specific epistemic artifact through the enactment of particular moves.

Collins and Ferguson introduce a number of forms and associated games, including *lists* (e.g., a list of subatomic particles), *hierarchical lists* (e.g., a taxonomy of the animal kingdom), *spatial* and *temporal decompositions* (e.g., a diagram of an electrical circuit and a model of the life cycle of a butterfly), *constraint equations* (e.g., Boyle's law), and *aggregate-behavior models* (e.g., an agent-based model of predator-prey dynamics). A temporal decomposition, for example, is a form that scientists use to understand the steps in a sequential process. Piaget's stage model of development is an example of a temporal decomposition, as is a model of the life cycle of a star. The simplest template for a temporal decomposition is a sequence of steps composing a longer process. Moves played to fill out the template include identifying meaningful steps in a larger process, dividing the process into those discrete steps, and arranging them in sequential order. More complicated temporal decompositions may include causal drivers to explain transitions between steps. To build these, the game entails additional moves, such as proposing a possible cause for the transition between each pair of steps.

The present work examines a child's engagement in a particular kind of theory-building game, focused on the construction of a computational agent-based model. In the computational agent-based modeling game, a player fills out a template structured by a computational agent-based modeling environment. The template requires them to write a program that, when run, simulates a complex systems phenomenon of interest. The program must specify the system's initial conditions, as well as the behavior of individual agents and their interactions. When the player runs the model, the individual agents behave according to the rules encoded in the program. Agent interactions ultimately lead to an emergent phenomenon at the aggregate level. The phenomenon's cause is not interpreted as due to any particular sequence of agent interactions and is instead understood as the outcome of countless random individual interactions. In this paper, our focal student builds a computational agent-based model of the spread of disease. An epidemic is an emergent phenomenon, which appears at the population level as a result of individuals' interactions at the agent-level.

2.2 Knowledge as a Complex System

The present work views knowledge as a complex system of elements drawn into networks depending on the sense-making demands of a given task or context. This view is described most precisely by the *knowledge in pieces* heuristic epistemological framework (KiP) [10]. KiP views the novice knowledge system as consisting of less rigidly structured and more context dependent networks than the expert knowledge system. It views the process of learning as a gradual "tuning toward expertise" [10] through which the more pliable and context-dependent novice knowledge system is reorganized and refined into the more coherent and rigid expert system. As such, the novice knowledge system is viewed as rich with *resources* for the construction of new knowledge [17,] [35]. This makes KiP an anti-deficit perspective [1]. A primary concern of the KiP enterprise is elaborating the framework with machinery for building computationally explicit models of human knowledge and learning.

Towards this, a number of KiP researchers have proposed ontologies of knowledge elements identified through grounded analyses of rich process data. These ontologies include elements of intuitive knowledge used to explain phenomena of our everyday experience, such as phenomenological primitives (p-prims) [10] like "more effort leads to more result." They include epistemological resources [17], such as "knowledge is truth taught to us by scientists and teachers." This work identifies elements of knowledge used by individuals to engage in theory-building games. This space of knowledge is called *meta-theoretic competence*.

2.2.1 *Meta-Theoretic Competence.*

Meta-theoretic competence (MTC) is a space of knowledge elements, which an individual draws on during their engagement in a theory-building game [38]. These elements serve different functions in the individual's enactment of the game's moves. Some elements *orient* the individual to the game and others *operationalize* the moves through which it is played. *Orienting elements* include epistemological resources, such as knowledge of the epistemic form and entry conditions for the game. *Operating elements* include knowledge elements that facilitate the execution of the moves through which the game is played. Operating elements share a family resemblance with skills and procedural knowledge [2]. These two kinds of knowledge elements work synergistically with *substantial knowledge* to facilitate an individual's engagement in an epistemic game (Figure 1). Substantial knowledge includes descriptive and explanatory knowledge elements, such as knowledge of facts and causal intuitions such as p-prims.

It is conjectured that each individual would bring a different space of meta-theoretic competence to the same theory-building game, reflecting their unique experience and education. It is further conjectured that each individual would bring a different space of meta-theoretic competence to different games, as each game has a different form, requires different moves, and is focused on explaining a different phenomenon. This paper presents a fine-grained investigation of the meta-theoretic competence one student brings to their engagement in a computational agent-based modeling game, identifying the moves they make and proposing elements of orienting and operating knowledge underlying those moves.

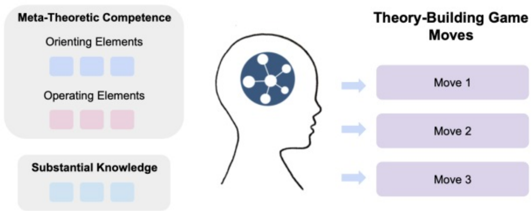

Figure 1: An individual's meta-theoretic competence is the space of knowledge they draw on to enact the moves of a theory-building game. It includes orienting and operating knowledge elements.

3 METHOD

This paper presents an instrumental case study to illustrate the meta-theoretic competence underlying a student's engagement in a computational agent-based modeling game. The case study is drawn from a larger study investigating middle school students' engagement in different approaches to scientific theory building, including the construction of computational agent-based models.

A practical goal of the larger project is to make computational agent-based modeling accessible to middle school students. The objective is to lower the threshold for participation in computational modeling so that science teachers might engage their students in the construction of scientific content knowledge through computational modeling practices. Towards this, the project has focused on designing block-based microworlds using the NetTango web interface [18]. NetTango makes the computational power of NetLogo [45] accessible to modelers by providing, for each model, a curated library of blocks that represent a narrow range of primitives needed for modeling a focal phenomenon. Previously called *semantic blocks* [51] and now called *domain blocks* [42], the blocks are, from a student's point of view, primitive elements of code that represent agents' actions, which can be combined to model a specific phenomenon. The project has designed domain-block libraries for simulating a number of complex systems phenomena, including the spread of disease [26], [47].

The empirical focus at the heart of the larger project is understanding how children use the blocks to engage in scientific theory building. The present study is focused on answering the question *"What knowledge do students draw on in their construction of computational agent-based models?"* More specifically, it is focused on understanding the meta-theoretic competence students draw on during their attempts to build, test, debug, and make sense of a model of a flu epidemic.

To address this question, a 1.5-hour interview with a middle school student called Sage was analyzed. Sage was 13 years old and had just started 8th grade at her local public school. Sage had previous experience with block-based programming, having participated in a one-day coding event at school where students were introduced to Scratch. The programming was not, however, used for the purpose of computational modeling. During the interview, Sage explored the *Spread of Disease* modeling microworld. Figure 2 shows the microworld with a model that has been built and initialized. The black box to the left is the *world*. The *world* shows the activity of the agents, which are programmed to behave

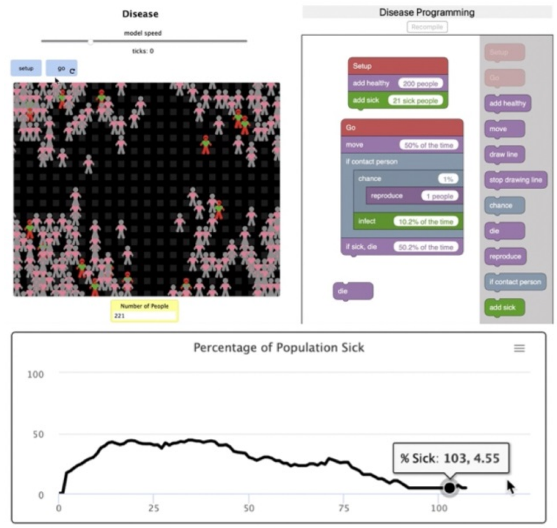

Figure 2: Spread of Disease microworld, featuring Sage's final model of Ebola, which she modified to produce her initial model of a flu epidemic.

according to the rules specified by the model. The *setup* and *go* buttons are controlled by procedures (red blocks), which the user must drag from the block library (far right) into the modeling field (middle) and then define by connecting with blocks (purple, gray, and green), such as *move*, *if contact person*, and *infect*. The box below the world and modeling field displays a graph of the percentage of the population that is sick, at any given point in time.

During the interview, Sage had command of the modeling microworld. The interviewer guided her through tasks and questions from a semi-structured protocol. The interview opened with an introduction of the microworld's features through open exploration. The interviewer then guided Sage through a sequence of modeling tasks, through which she modeled the spread of each of several diseases of her own choice. The interviewer prompted Sage to begin each task and then asked questions to understand the motivation and reasoning behind the moves she made as she engaged in the task.

The interview with Sage was video- and audio-recorded and her interaction with the microworld was captured by recording the computer screen. The audio recording was transcribed and analyzed along with the screencast using a fine-grained grounded approach, called *knowledge analysis* [13]. The knowledge analysis was directed at identifying the knowledge underlying Sage's theory-building activity, with a particular focus on identifying evidence of orienting and operating elements of meta-theoretic competence.

The analysis proceeded as follows. First, the screencast of Sage's interview was reviewed to identify episodes during which she engaged in building models for particular diseases, including Ebola, flu, and a zombie apocalypse. The flu episode was selected for further analysis, and decomposed into steps of *model building*, *testing*, *sense-making*, and *debugging*. These steps were organized sequentially, to preserve their temporal order. Over the course of the 17 minutes that Sage worked on her model of the spread of flu, she refined her model across six drafts. For this paper, one cycle of model building, testing, sense-making and debugging was selected for analysis. For each step, transcription of Sage's utterances and verbal interactions with the interviewer were analyzed to determine her moves. Her moves were then explained in terms of meta-theoretic competence, as motivated by particular elements of orienting knowledge and facilitated by particular elements of operating knowledge. Below is the temporal decomposition of Sage's first four steps in modeling a flu epidemic, highlighting the meta-theoretic competence she drew on to play her computational agent-based modeling game.

4 FINDINGS

Sage sits at a desk in an office with the interviewer at her left. She faces a laptop screen, viewing the *Spread* of *Disease* modeling microworld. She has been exploring the microworld for 40 minutes. She began with open exploration, experimenting with different combinations of blocks and observing the resulting activity in the world. At the interviewer's request, she turned her attention to building and debugging a model of Ebola. Having produced a model that matched her expectations of the disease, the interviewer asks Sage how she would modify the code to model the spread of flu. Figure 2 (above) shows Sage's final model of Ebola, which she modifies to model the spread of flu. Sage's modeling activity is presented below, as a piecewise trajectory of four steps. Each step is illustrated with transcript and presents a summary of her moves. Elements of orienting and operating knowledge are then proposed (in italics), which are conjectured to underlie her enactment of moves. Figures are then presented to visually summarize the knowledge used by Sage in her enactment of each move.

4.1 Step 1: Building the Initial Model

Sage examines the model of Ebola, considering how to modify the code to model the spread of flu.

> Sage: If it was flu, hmm, it's less deadly.
>
> Interviewer: OK
>
> Sage: Like, I don't know, like 10%. [Sage decreases the deadliness parameter from 50.2% to 10% to 5.5%]

In this step, Sage determines that flu is less deadly than Ebola and adjusts the probability that a sick agent will die, purposefully selecting a new parameter value. She indicates some uncertainty regarding the parameter value, qualifying her choice with the words "I don't know." Her moves and utterances suggest she is drawing on a rich space of meta-theoretic competence and substantial knowledge (Figure 3). She orients to her activity with a goal set by the interviewer: to *modify the Ebola code to model the spread of flu.* She appears to have heuristic knowledge that the *deadliness parameter for Ebola can be modified to model the spread of flu.* This leads to a sub-goal: to *determine the deadliness of flu, relative to Ebola.* Her determination of the deadliness of flu with respect to Ebola indicates the existence of operating knowledge facilitating her *comparison of the deadliness of Ebola with the deadliness of flu*, and substantial knowledge regarding the *deadliness of Ebola and flu.* Sage's purposeful selection of a new value for the deadliness parameter indicates that she is orienting to the move with the goal of *modifying the deadliness parameter to model the spread of flu.* The move also indicates the existence of substantial knowledge determined by her previous move, that *flu is less deadly than Ebola*, and operating knowledge facilitating her *purposeful adjustment of the slider*, to decrease the deadliness parameter. Her recognition of her own uncertainty regarding the appropriate value of the parameter indicates a kind of metacognition, an *awareness of the limits of her own knowledge*, and her utterance "like 10%," suggests she knows that *approximation is a productive heuristic* for modeling.

4.2 Step 2: Testing the Initial Model

The interviewer asks Sage how she thinks her modification is going to influence the model outcome.

> Sage: . . . I think the epidemic is going to spread like much further because, um, people like when people are moving around and infecting people, they're like, they're, they're not, they don't have like a 50% chance of dying every time. [...] And so people weren't, people were dying faster than they were coming in contact with people instead of. . .

In testing her initial model, Sage demonstrates a rich space of meta-theoretic competence and substantial knowledge (Figures 4 and 5). She makes a prediction for the outcome of the model run, comparing her expectation with results of previous runs of her model of Ebola and explaining the aggregate-level outcomes of those runs as the result of agent-level interactions. Her cognitive activity is driven by the interviewer, who has oriented her to her work with the goal of *predicting how the modified code will change the model outcome.* This goal entails a sub-goal of *comparing her prediction for the outcome of the flu model with the outcome of Ebola.* Sage's prediction further suggests she has orienting knowledge that *mental simulation can lead to realistic outcomes.* Operating knowledge facilitates her *mental simulation of the flu model*, and her *comparison of her imagined outcome of the flu model with the observed outcome of the Ebola model.* Her mental simulation also entails substantial knowledge of the *effects of her models' parameters on agent behavior.* Sage's explanation for the aggregate-level outcome as a result of agent-level interactions suggests she is orienting to the move with an aesthetic that it is *important to explain the reasoning behind her prediction*, which makes *explaining her reasoning* a goal. Her explanation suggests operating knowledge facilitating her *connection of the observed aggregate-level phenomenon and agent-level behaviors.* In explaining the causal relationship, Sage appears to be drawing on substantial knowledge she constructed while modeling Ebola, that *if a disease is deadly to an infected individual it will kill carriers before they can spread it to the rest of the population.*

Sage presses the "go" button, running the model to test her prediction. She observes the model run, watching as the total number of people in the world decreases as healthy people become infected and sick people die. Running the model to test her prediction suggests Sage orients to her activity with the aesthetic that *a hypothesis should be tested*, which makes *testing her prediction* a goal. It also suggests operating knowledge facilitating her *start of the simulation.* Her observation suggests she orients to the model with the expectation that it will *produce meaningful results*, which motivates a goal of observing the model run, and has operating knowledge that *directs her attention to the visual displays of the simulation interface.* The outcome she observes contrasts with her Ebola model, where

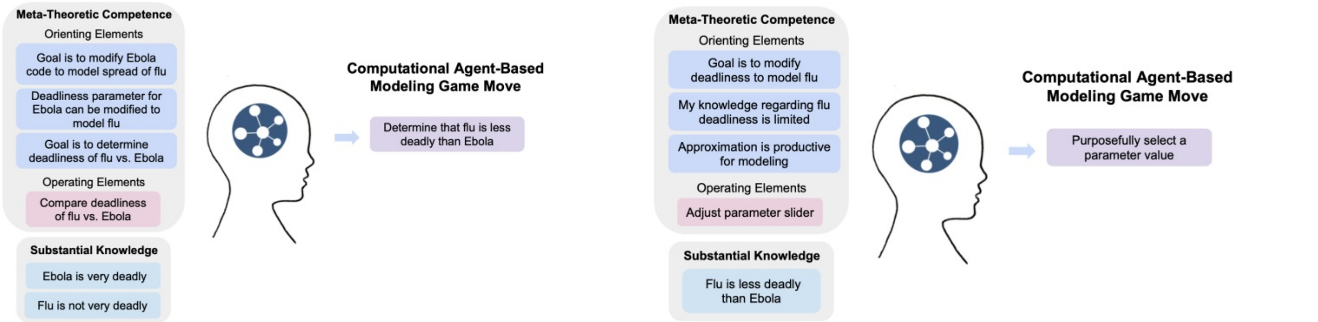

Figure 3: Left: The knowledge Sage draws on to determine that flu is less deadly than Ebola. Right: The knowledge Sage draws on to purposefully select a new parameter value.

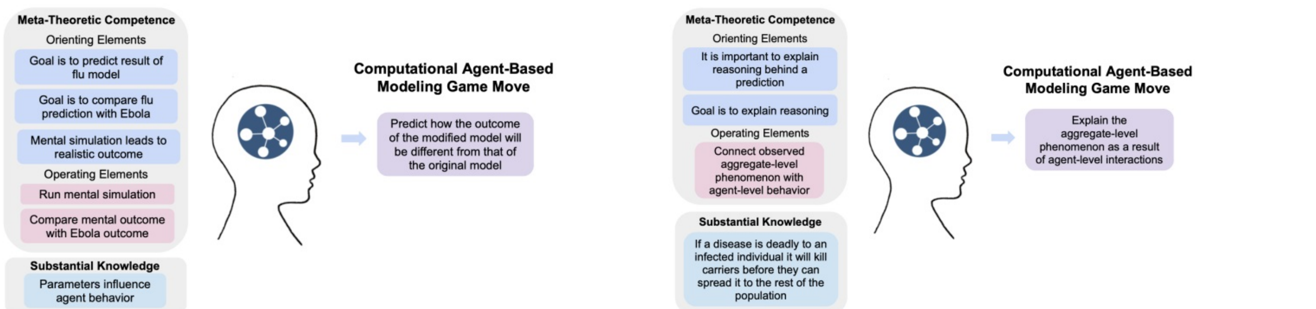

Figure 4: Left: The knowledge Sage draws on to predict how the outcome of the modified model will be different from that of the original model. Right: The knowledge Sage draws on to explain the aggregate-level phenomenon as a result of agent-level interactions.

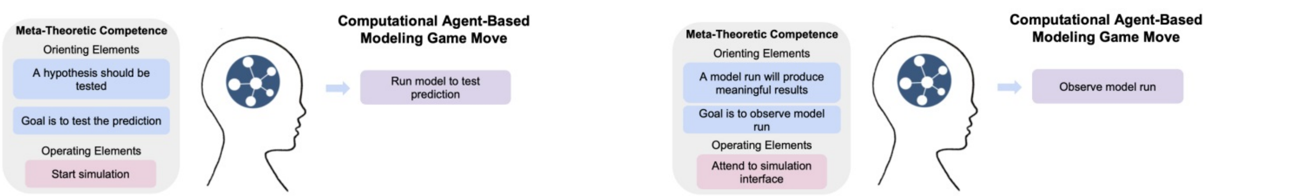

Figure 5: Left: The knowledge Sage draws on to run the model and test her prediction. Right: The knowledge Sage draws on to observe the model run.

all of the initially sick people died in the first few ticks of the model run, leaving the rest of the population untouched and healthy.

4.3 Step 3: Making Sense of the Initial Model

The interviewer asks Sage if this model looks different from her model of Ebola.

> Sage: Yeah. Um, I think the percentage of population is like going down as you can see. [Sage points at the graph]
>
> Interviewer: Ah, so what did you change in the um, the flu case?
>
> Sage: Well, people died less and it spread less. And so, we went from like 221 people, 41 people because it's, um, it's very infectious, but it's like, like people don't die a lot. But when there are a lot of people then people start dying. And then no one's, then there's a less chance of getting infected. And so just people keep dying and then eventually [...] So, because no one's recovering, you can't, I didn't have it set to recover.

In this step, Sage describes the flu model's outcome and compares it with the outcome of the Ebola model. She interprets the graph to understand what is happening at the aggregate-level, noting that the population is decreasing over time and that 41 people have died in this simulation, which she calculates using information from the initial conditions programmed in the setup code and information displayed in a box in the interface titled "number of people." She compares the results of this run with results of the previous runs of the Ebola model. She explains the aggregate-level outcome in

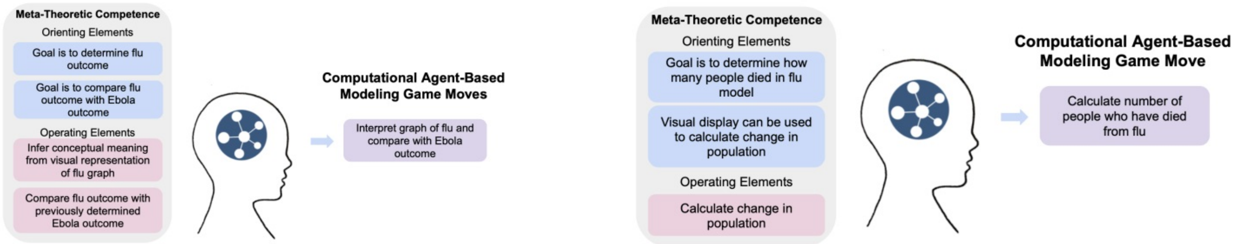

Figure 6: Left: The knowledge Sage draws on to interpret the graph of flu and compare it with Ebola. Right: The knowledge Sage draws on to calculate the number of people who have died from the flu epidemic.

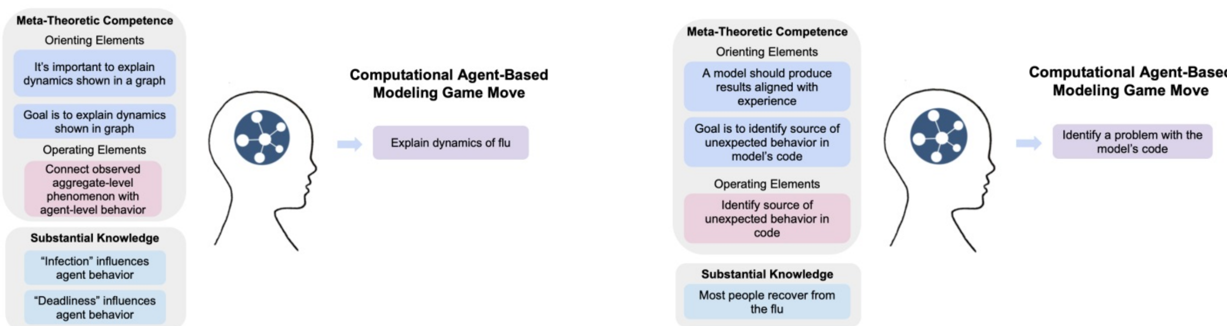

Figure 7: Left: The knowledge Sage draws on to explain the dynamics of the flu epidemic. Right: The knowledge Sage draws on to identify a problem with the model's code.

terms of agent-level behavior, expressing that the model of flu produced a different aggregate-level outcome from the model of Ebola because flu is less deadly than Ebola, to infected individuals. Through her sense-making, Sage arrives at a powerful conclusion about complex-systems dynamics: when a disease is deadly to an infected individual, infected people die quickly and "there's a less chance of getting infected." Flu is less deadly, so the disease is able to spread to more of the population and ultimately kill more people. Sage acknowledges that the population may have decreased too much, because the only option for sick people is to eventually die, as she left out of the model the possibility of recovering by leaving out the "recover" block. In noting this, Sage connects the agent behavior with the model code.

In making sense of the model, Sage demonstrates a rich space of meta-theoretic competence (Figures 6 and 7). Her interpretation of the graph and comparison with the Ebola model's outcome is driven by orienting knowledge, which is the goal (given to her by the interviewer) of *comparing the flu model's outcome with the outcome of the Ebola model.* This goal entails a sub-goal of *determining the flu model's outcome.* Her interpretation of the graph is executed by operating knowledge, which allows her to infer *conceptual meaning from the visual representation of the graph.* Her comparison of the flu model's outcome with that of Ebola is facilitated by operating knowledge executing that *comparison.* Her calculation of the number of people who had died suggests she orients to the task with the goal of *understanding how many people died in the flu model as compared with Ebola*, along with heuristic knowledge of how *the visual display can be used to calculate changes in population.* It suggests operating knowledge executing the *calculation of change in population.*

Her explanation for the dynamics of the flu epidemic indicate orienting knowledge, in the form of an aesthetic, that *it is important to explain the dynamics shown in the graph.* This motivates *explanation* as a goal. Operating knowledge works in coordination with substantial knowledge about the *effect of the model's parameters on agent behavior* to facilitate her *determination of a causal connection between the agent-level interactions observed in the world with the change in population observed at the aggregate level*, represented by the graph. Finally, her identification of a problem with the model's code indicates that she orients to the task with the expectation that *the model should produce results that align with experience*, which in this case, is encoded in substantial knowledge that *people usually recover from flu.* This motivates the goal of *identifying the source of the unexpected behavior in the code*, which is facilitated by operating knowledge.

4.4 Step 4: Debugging the Initial Model

The interviewer asks Sage if she thinks as many people die in a flu epidemic as shown in her model.

> Sage: Probably not. It's probably because I have the infectivity high and people aren't recovering. But let's say you recover like, I don't know, 50%? No, like 75 but that's going to be way too high. Yeah, 75 and less infectious, and this will be hard to start your... Wait, no, that's recover, wait. Yeah. Infect like 10%.

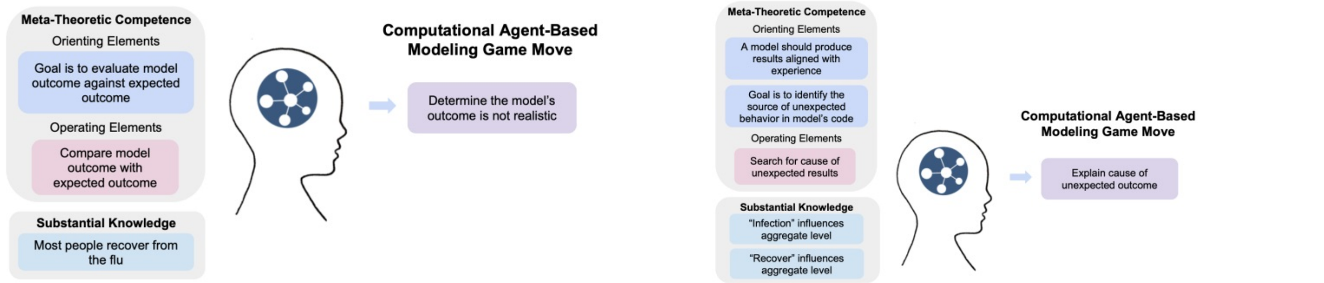

Figure 8: Left: The knowledge Sage draws on to determine that the model's outcome is not realistic. Right: The knowledge Sage draws on to explain the cause of the unexpected outcome.

At the interviewer's prompting, Sage determines that her model's results are not realistic. She explains the unexpected outcome as the result of an incorrect parameter setting and resulting agent-behavior. She modifies the code to address the problem, adding the "recover" block to the model and sliding the parameter value to 73.1%. She also modifies a parameter to address the problem, changing the probability of infection to 10.5%. In debugging her model, Sage demonstrates a rich space of meta-theoretic competence (Figures 8 and 9). Sage's determination of her model's results as unrealistic is motivated by orienting knowledge of the goal (set by the interviewer) to *assess her model's performance against her own expectations*, and facilitated by operating knowledge, executing her *comparison of the model results with her expectations*, which are based on substantial knowledge that *most people recover from flu*. Her explanation of the unexpected outcome suggests she orients to the task with the expectation that the *model should produce results aligned with her experience*, which gives her the goal of *identifying the source of the unexpected results*. This motivates her *search for the cause of unexpected results in her model*, which is facilitated by operating knowledge. She arrives at an explanation by drawing on substantial knowledge about the *aggregate-level dynamics caused by a high infection rate and a recovery rate of zero*, which she developed through her exploration of the model.

Having determined a potential cause, Sage orients to her activity with the goal of modifying the model *to obtain results aligned with her expectations*. Her modification is facilitated by operating knowledge executing *her addition of the "recover" block*, her *purposeful selection of a high recovery rate* and her *decrease of the probability of infection parameter*. Her modification of the model through adding the "recover" block, selecting a high recovery rate, and decreasing the infection probability parameter is not based on prior knowledge of infection or recovery rates for flu, but rather, substantial knowledge of *how each factor controls the behavior of individual agents*, and a growing sense for *how the interactions at the agent level lead to results at the aggregate level*. Her attempt at debugging is more of a reactive, "guess-and-test" tinkering, to see which parameters need to be involved and to what values they must be set.

4.5 Step 5 – Step 22: Testing, Debugging, and Making Sense of the Model

From this point forward, Sage continues to refine her model of flu, engaging in another 18 steps of debugging, testing, and making sense of model outcomes. The remaining steps feature most of the same theory-building moves seen in the first 4 steps. In further attempts at debugging, Sage modifies several parameters, decreasing the recovery parameter again, increasing the infection parameter, and decreasing the number of initially healthy people. She tests the model after each parameter adjustment and observes the model run to see if the modification solves her problem. She describes the aggregate-level outcome of the model run and tries to explain it in terms of agent-level behavior and interactions. She references numerical data a number of times and does calculations in her head to assess whether the results are realistic. Towards the end of the activity, she slows down the model run to get a better sense for what is happening at the agent level. She also engages in purposeful exploration by comparing multiple trial runs, declaring that she wants to "collect a dataset." In total, Sage spends 17 minutes refining her model across six drafts. She demonstrates evidence of a rich space of meta-theoretic competence, engaging in sophisticated modeling moves that may be motivated and facilitated by elements of orienting and operating knowledge.

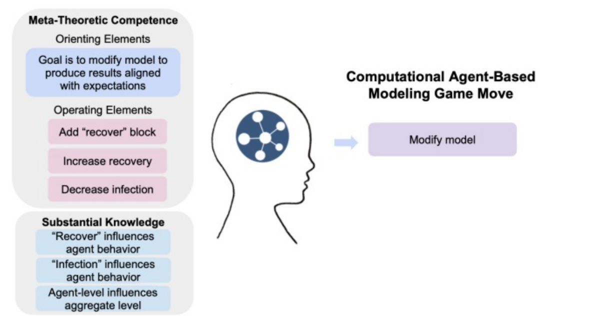

Figure 9: The knowledge Sage draws on to modify her model.

5 DISCUSSION

This paper presented a systematic investigation of the moves one student enacted during her engagement in a computational agent-based modeling game. A slice of the student's work building, testing, making sense of, and debugging a model of a flu epidemic was analyzed. The episode was divided into 4 discrete steps and candidate elements of meta-theoretic competence were identified, including orienting knowledge motivating her moves and operating knowledge facilitating their enactment.

5.1 Contributions

The analysis of Sage's construction of a model of a flu epidemic suggests she has a wealth of knowledge resources for engaging in the computational agent-based modeling game. This finding makes an empirical contribution to literature concerned with using computational agent-based modeling to teach science by building on students' intuitive resources [3], [43]. While previous work has characterized content knowledge and skills students bring to their productive participation in computational modeling activities [39], [40], [52], the present work offers a high-resolution characterization of the knowledge underlying one student's construction of an agent-based computational model. Importantly, the work characterizes the knowledge motivating and facilitating the *moves* made by the student in their enactment of a computational agent-based modeling game. In this way, the work extends the KiP framework with theoretical machinery for characterizing knowledge underlying students' participation in computational modeling practices. It also contributes to the broader discussion on engaging students in authentic science practices [14], [28] by identifying resources, which can be refined into scientific practices. In this way, the paper joins the critical efforts of researchers urging educators and education researchers to view students through an anti-deficit lens and see their knowledge and activity as on a continuum with that of expert scientists [1], [4], [31].

Finally, the paper makes a practical contribution to the design of activities scaffolding students' engagement in computational agent-based modeling practices. Identifying the knowledge resources students bring to their productive engagement in modeling can help researchers design activities that intentionally draw out and develop those resources into more sophisticated computational modeling practices. For example, the analysis of the moves made by Sage in building her initial model suggest that certain elements of meta-theoretic competence facilitated her productive engagement. These include orienting elements such as the goal of the task, heuristic knowledge that one can modify the code of an existing model to produce a new model and that approximation is productive in modeling, and the aesthetic that a hypothesis should be tested. These also include operating elements such as the ability to interpret a graph or purposefully manipulate a model's parameters. Activities in computational modeling microworlds could be designed to intentionally elicit such knowledge from students in the context of guided explorations and then help them reflect on and develop it.

5.2 Limitations

While the results of this work can inspire the design of constructivist computational learning environments and associated activities, it is important to recognize the limitations of the study. First, it examines data taken from one interview with one student. The results would likely have been different if a different student had been interviewed or different prompts or microworld had been used with the same student. Second, the data provide limited depth and insight into the student's knowledge. While rich interactions between the student and microworld were captured, the analysis attempts to go beyond merely describing observable moves and explain those moves in terms of knowledge, which cannot be seen but only inferred. As the construct of meta-theoretic competence is in its infancy, so are methods for identifying and characterizing it. It is therefore important to acknowledge the speculative nature of the paper's analysis. Despite this, the work is a step in a productive direction. It is a fundamental assumption of KiP that knowledge must underlie all thinking and purposeful action, and while it is challenging to empirically study the knowledge involved in individuals' engagement in epistemic games, it is important to find ways to study that knowledge and build theoretical models of it.

REFERENCES

[1] Adiredja, A. P. (2019). Anti-deficit narratives: Engaging the politics of research on mathematical sense making. *Journal for Research in Mathematics Education*, *50*(4), 401-435.

[2] Anderson, J. R. (1996). ACT: A simple theory of complex cognition. *American psychologist*, *51*(4), 355.

[3] Aslan, U., LaGrassa, N., Horn, M., & Wilensky, U. (2020, June). Phenomenological Programming: a novel approach to designing domain specific programming environments for science learning. In *Proceedings of the Interaction Design and Children Conference* (pp. 299-310).

[4] Bang, M., Warren, B., Rosebery, A. S., & Medin, D. (2013). Desettling expectations in science education. *Human Development*, *55*(5-6), 302-318.

[5] Bielik, T., Fonio, E., Feinerman, O., Duncan, R. G., & Levy, S. T. (2021). Working together: Integrating computational modeling approaches to investigate complex phenomena. *Journal of Science Education and Technology*, *30*, 40-57.

[6] Collins, A., & Ferguson, W. (1993). Epistemic forms and epistemic games: Structures and strategies to guide inquiry. *Educational psychologist*, *28*(1), 25-42.

[7] Costanza, R., & Gottlieb, S. (1998). Modelling ecological and economic systems with STELLA: Part II. *Ecological Modelling*, *112*(2-3), 81-84.

[8] Damelin, D., Krajcik, J. S., Mcintyre, C., & Bielik, T. (2017). Students making systems models. *Science Scope*, *40*(5), 78-83.

[9] De Andrade, V. F., Freire, S., & Baptista, M. (2021). Constructing Scientific Explanations for Chemical Phenomena through Drawings among 8th-Grade Students. *Eurasia Journal of Mathematics, Science and Technology Education*, *17*(1).

[10] diSessa, A. A. (1993). Toward an epistemology of physics. *Cognition and instruction*, *10*(2-3), 105-225.

[11] diSessa, A. A. (1995). Designing Newton's laws: Patterns of social and representational feedback in a learning task. In *Dialogue and Interaction: Modeling Interaction in Intelligent Tutoring Systems.* (pp. 105–122). Springer-Verlag.

[12] diSessa, A.A. (2001). Changing minds: Computers, learning, and literacy. MIT Press.

[13] diSessa, A. A., Sherin, B., & Levin, M. (2016). Knowledge analysis: An introduction. A. diSessa, M. Levin, & N. Brown (Eds.), Knowledge and interaction: A synthetic agenda for the learning sciences, 30-71.

[14] Ford, M. (2008). 'Grasp of practice as a reasoning resource for inquiry and nature of science understanding. *Science & Education*, *17*(2), 147-177.

[15] Foster, I. (2006) 2020 computing: a two-way street to science's future. Nature 440(7083):419

[16] Hammer, D. (2000). Student resources for learning introductory physics. *American journal of physics*, *68*(S1), S52-S59.

[17] Hammer, D., & Elby, A. (2012). On the form of a personal epistemology. In *Personal epistemology* (pp. 169-190). Routledge.

[18] Horn, M.S., Baker, J. & Wilensky, U. (2020). NetTango Web [Computer Software]. Evanston, IL: Center for Connected Learning and Computer-Based Modeling, Northwestern University.

[19] Kenyon, L.O., Schwarz, C.V., Hug, B., & Baek, H. (2008). Incorporating modeling into elementary students' scientific investigations. Paper presented at the annual meeting of the National Association for Research in Science Teaching, Baltimore, MD.

[20] Krist, C., Schwarz, C., & Reiser, B. (2019). Identifying essential epistemic heuristics for guiding mechanistic reasoning in science learning. *The Journal of the Learning Sciences*, *28*(2), 160–205.

[21] Lehrer, R., & Schauble, L. (2002). Distribution: A resource for understanding error and natural variation. In *Sixth International Conference on Teaching Statistics (ICOTS6), Cape Town.*

[22] Lehrer, R., Schauble, L., & Lucas, D. (2008). Supporting development of the epistemology of inquiry. *Cognitive development*, *23*(4), 512-529.

[23] Lindgren, S., Morris, K., & Price, A. (2021). Designing environmental storylines to achieve the complementary aims of environmental and science education through science and engineering practices. *The Journal of Environmental Education*, *52*(4), 239-255.

[24] Louca, L.T., & Zacharia, Z.C. (2012). Modeling-based learning in science education: cognitive, metacognitive, social, material and epistemological contributions. Educational Review, 64(4), 471-492.

[25] Manz, E. (2012). Understanding the Codevelopment of Modeling Practice and Ecological Knowledge. *Science Education*, *96*(6), 1071–1105.
[26] Martin, K., Swanson, H., Sherin, B., Wilensky, U. (2020). NetTango Disease Spread and Prevention model. http://ccl.northwestern.edu/theorybuilding/Siyu-Intervention/Model5Disease.html.~ Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
[27] NGSS Lead States (2013) Next generation science standards: for states, by states. The National Academies Press, Washington, DC.
[28] Osborne, J. (2016). Defining a knowledge base for reasoning in science: the role of procedural and epistemic knowledge. In R. A. Duschl & A. S. Bismack (Eds.) Reconceptualizing STEM education: The central role of practices. New York: Routledge.
[29] Passmore, C., & Stewart, J. (2002). A modeling approach to teaching evolutionary biology in high schools. *Journal of Research in Science Teaching*, *39*(3), 185–204.
[30] Perkins, K., Adams, W., Dubson, M., Finkelstein, N., Reid, S., Wieman, C., & LeMaster, R. (2006). PhET: Interactive simulations for teaching and learning physics. *The physics teacher*, *44*(1), 18-23.
[31] Rosebery, A. S., Ogonowski, M., DiSchino, M., & Warren, B. (2010). "The coat traps all your body heat": Heterogeneity as fundamental to learning. *The Journal of the Learning Sciences*, *19*(3), 322-357.
[32] Samon, S., & Levy, S. T. (2017). Micro–macro compatibility: When does a complex systems approach strongly benefit science learning? *Science Education*, *101*(6), 985-1014.
[33] Schwarz, C. V., Passmore, C., & Reiser, B. J. (2017). Helping students make sense of the world using next generation science and engineering practices. NSTA Press.
[34] Sinha, R., Swanson, H., Date, G., & Chandrasekharan, S. (2024). Epistemic games at the frontier: A characterization of emerging STEM practices to design K12 makerspaces. *Proceedings of the 18th International Conference of the Learning Sciences* - ICLS 2024 (4pgs). Buffalo, NY: International Society of the Learning Sciences.
[35] Smith III, J. P., diSessa, A. A., & Roschelle, J. (1994). Misconceptions reconceived: A constructivist analysis of knowledge in transition. *The journal of the learning sciences*, *3*(2), 115-163.
[36] Suppe, F. (1974). The search for philosophic understanding of scientific theories: Introduction. In Kuhn, T. S., & Suppe, F. (Eds.), *The structure of scientific theories* (p.244-254). Chicago: University of Illinois Press.
[37] Svoboda, J., & Passmore, C. (2013). The Strategies of Modeling in Biology Education. *Science & Education*, *22*, 119–142.
[38] Swanson, H. (2022). Meta-theoretic competence demonstrated by students in the Patterns class. In Chinn, C., Tan, E., Chan, C., & Kali, Y. (Eds.), *Proceedings of the 16th International Conference of the Learning Sciences* - ICLS 2022 (pp. 679-686). Hiroshima, Japan: International Society of the Learning Sciences.
[39] Swanson, H., Arastoopour Irgens, G. A., Bain, C., Hall, K., Woods, P., Rogge, C., Horn, M., & Wilensky, U. (2018). Characterizing computational thinking in high school science. In Kay, J. and Luckin, R. (Eds.), *Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences* (ICLS 2018), Volume 2, Short Papers, Symposia, and Selected Abstracts, (pp. 871-878). London, UK: International Society of the Learning Sciences.
[40] Swanson, H., Sherin, B., & Wilensky, U. (2021). Characterizing student theory building in computational modeling. In de Vries, E., Ahn, J., & Hod, Y. (Eds.), *15th International Conference of the Learning Sciences* - ICLS 2021 (pp. 745-748). Bochum, Germany: International Society of the Learning Sciences.
[41] Tinker, R. F., & Xie, Q. (2008). Applying computational science to education: the molecular workbench paradigm. *Computing in Science & Engineering*, *10*(5), 24-27.
[42] Wagh, A., Cook-Whitt, K., & Wilensky, U. (2017). Bridging inquiry-based science and constructionism: Exploring the alignment between students tinkering with code of computational models and goals of inquiry. *Journal of Research in Science Teaching*, *54*(5), 615-641.
[43] Wagh, A., Fuhrmann, T., Eloy, A. A. D. S., Wolf, J., Bumbacher, E., Blikstein, P., & Wilkerson, M. (2022, June). MoDa: Designing a tool to interweave computational modeling with real-world data analysis for science learning in middle school. In *Proceedings of the 21st Annual ACM Interaction Design and Children Conference* (pp. 206-211).
[44] Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of science education and technology*, *25*, 127-147.
[45] Wilensky, U. (1999a). NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
[46] Wilensky, U. (1999b). GasLab—An extensible modeling toolkit for connecting micro-and macro-properties of gases. In *Modeling and simulation in science and mathematics education* (pp. 151-178). New York, NY: Springer New York.
[47] Wilensky, U. (2005). NetLogo Disease Solo model. http://ccl.northwestern.edu/netlogo/models/DiseaseSolo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
[48] Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. *Journal of Science Education and technology*, *8*, 3-19.
[49] Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and instruction*, *24*(2), 171-209.
[50] Wilkerson-Jerde, M. H., Gravel, B. E., & Macrander, C. A. (2015). Exploring shifts in middle school learners' modeling activity while generating drawings, animations, and computational simulations of molecular diffusion. *Journal of Science Education and Technology*, *24*, 396-415.
[51] Wilkerson-Jerde, M., & Wilensky, U. (2010). *Restructuring Change, Interpreting Changes: The DeltaTick Modeling and Analysis Toolkit.* Paper presented at the Constructionism 2010 Conference, Paris.
[52] Wu, S., Swanson, H., Sherin, B., & Wilensky, U. (2022). Students' prior knowledge of disease spread and prevention. In Chinn, C., Tan, E., Chan, C., & Kali, Y. (Eds.), *Proceedings of the 16th International Conference of the Learning Sciences* - ICLS 2022 (pp. 1241-1244). Hiroshima, Japan: International Society of the Learning Sciences.